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A Prospective Payment System for Inpatient Rehabilitation

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PREFACE

This report describes the construction of a model Prospective Payment System (PPS) for Medicare inpatient rehabilitation cases. It evaluates the possible PPS with respect to its ability to match payments to cost at the case and hospital level and with respect to the financial risk that the system imposes on rehabilitation facilities. A companion report describes the representativeness of our dataset and the evaluation of the case classification system that we recommend for use in the rehabilitation PPS. The report on the classification system is:

Grace M. Carter, Daniel A. Relles, and Joan L. Buchanan, *A Classification System for Inpatient Rehabilitation Patients: A Review and Proposed Revisions to the Functional Independence Measure--Function Related Groups*, RAND, PM-682-HCFA, 1997.

This report and the companion report cited above constitute the final report for delivery order number 9 under Master Contract Number 500-92-0023 between the Health Care Financing Administration and RAND.

The classification system is based heavily on the Functional Independence Measure--Function Related Groups (FIM/FRG) classification system developed by Margaret Stineman and colleagues at the University of Pennsylvania and SUNY-Buffalo. Both the classification report and this report use the Uniform Data System for medical rehabilitation (UDSmr^{SM}), which was created and is maintained by the Uniform Data System for Medical Rehabilitation (UDSMR), a division of University of Buffalo Foundation Activities, Inc. This division operates within the Center for Functional Assessment Research (CFAR), under the Department of Rehabilitation Medicine of the School of Medicine and Biomedical Sciences of the State University of New York at Buffalo. The UDSmr^{SM} contains discharge records from participating hospitals and these discharge records include the Functional Independence Measure or FIM^{SM}, a service mark of the UDSMR.

UDSmr owns all copyrights to the FIM^{TM} measurement instrument (i.e., the Uniform Data Set, the Functional Independence Measure scale, the related impairment codes and the Guide for Use of the Uniform

Dataset for Medical Rehabilitation), and to all databases of patient data compiled using the FIM™ measurement instrument. FIM™ is UDSmr's trademark used in connection with its measurement instrument and databases; FIM℠ is UDSmr's service mark used in connection with its data management service. Appropriate Licenses are available from UDSmr to qualified health facilities, researchers and consultants.

All copyrights and related intellectual property rights in the Function Related Group ("FRG") classification system, including trade secrets and proprietary information ("FRG Information"), are owned by The University of Pennsylvania. UDSmr has the exclusive worldwide license to use the FRGs and the FRG Information for the development, creation, sale, distribution, and use of products or services incorporating any portion of the foregoing.

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SUMMARY

Inpatient rehabilitation, an important component of care for Medicare beneficiaries, has been growing rapidly. A Rehabilitation Prospective Payment System (RPPS) would improve in several ways on current payments for inpatient rehabilitation. The current payment system treats new facilities differently from older ones and may have contributed to the increase in Medicare costs. Because payments in an RPPS would be based on national standards rather than on the hospital's own historical costs, an RPPS would eliminate this inequity, provide more incentive to expensive providers to control costs, and eliminate the ability for hospitals to increase payments by increasing costs.

We developed a model of such an RPPS, examining each element of such a system: case classification, case weights, hospital-level payment adjustments, and a monitoring system. We developed special payment arrangements for unusual patients including transfer cases, high cost (outlier) cases, and very low cost cases.

We evaluated the chosen RPPS model and various alternatives by simulating payment. The simulations assumed that the payment method would not affect behavior. We evaluated each alternative with respect to (1) the accuracy with which it matches payment to cost for individual patients, (2) the accuracy with which it matches payment to cost for hospitals, (3) whether payments are close to costs for large groups of hospitals defined by specific characteristics (geographic location, type of facility, teaching hospitals, etc.), (4) whether the payments are close to cost for particular groups of patients, and (5) the financial risk associated with random variation in patient case costs.

PAYMENT ELEMENTS OF AN RPPS

Case Classification

Patients are classified based on their Function Related Group (FRG) and the presence of comorbidities. FRGs are based in turn on the patients' clinically defined Rehabilitation Impairment Category (RIC) and functional status at admission, as measured by the Functional Independence Measure (FIM). The FIM-FRGs were originally developed by

researchers at the University of Pennsylvania and SUNY-Buffalo, and we use a slightly modified version that includes a split between cases with and without specified comorbidities.

Relative Weights

Relative weights are calculated for each FRG and Comorbidity (FRGC) combination so that the weights are proportional to the resources used by the typical patient in the FRGC. Payment for each patient is proportional to the weight for the FRGC. We examined a variety of techniques for calculating these weights but found them similar.

Hospital Payment Factors

The payment rate for each hospital is adjusted for justifiable differences in cost that are beyond the control of the hospital manager. We tested the relationship among costs and factors that are suitable for payment as evidenced by the fact that the factors are actually used for payment in the acute care PPS: area wages, the teaching program, the low income population, and an indicator for large urban area. We found substantial effects on costs from the wage index and the proportion of Medicare patients who are eligible for Medicaid. Although we found no effect of the teaching program, we recommend revisiting this question with verified data on the population of all rehabilitation teaching hospitals. Future analyses should also address whether there is an interaction between teaching status and the percentage of low income population or inner city location.

Transfer Cases

We recommend paying each transfer case a per diem amount equal to the average daily payment for a full case in the same FRGC plus an extra amount equal to 50 percent of the per diem. This method will result in short-stay transfer cases receiving payment that approximates the cost of treatment received and should be relatively robust to changes in the case weight.

Outlier Cases

Extra payment for outlier cases strongly improves accuracy at the patient and hospital level. Such payment reduces financial risk that would otherwise be substantial due to the relatively small size of many rehabilitation facilities. It reduces losses caused by very expensive patients and therefore reduces incentives to underserve such patients. Payment reductions for very low cost cases allow an even better match of payments to costs and reduce incentives for unnecessary or futile admissions.

Implementation Problems in an RPPS

If an RPPS were to be implemented, HCFA must plan for improvements in coding. It is likely that there are errors of omission in the comorbidity indicator. If exempt unit discharge records are coded by the same medical record technicians who code the hospital's PPS records, then we would expect that omission errors would be less frequent in exempt units than in freestanding facilities. Our analysis suggests that exempt units do code better. There may also be coding errors in the FIM because these items have not been used for payment either. In the long run, better coding would result in fairer payments.

The greater cost control incentives derived from an RPPS might result in premature discharge of some cases, thus producing either quality of care problems, increased Medicare expenditures for additional care, or both. If LOS declines under an RPPS, it would be necessary to determine whether the decline was due to the elimination of unnecessary days or to inappropriate discharge. We suggest the possibility of using two outcomes to monitor whether a decline in LOS affected quality of care: functional gain between admission and discharge and whether the patient resides in a skilled nursing facility (SNF) within 30 days of discharge from rehabilitation. For each outcome, we show that the FIM and/or FIM/FRGs are important predictors of outcome and could be the basis of risk adjustment for a hospital index. We also found substantial differences across hospitals in risk-adjusted outcomes.

CONCLUSIONS

We conclude that an RPPS is feasible. The design used here appears to achieve its goals. The RPPS provides hospitals with incentives for efficiency because they can keep payments in excess of costs. The RPPS explains about 50 percent of patient-level costs and disadvantages no demographic group, and therefore should maintain access for all Medicare beneficiaries to high quality and appropriate care. Depending on the details of the RPPS, payments explain 60 to 65 percent of the variance in costs at the hospital level. The only hospital group systematically disadvantaged by the RPPS are new hospitals that are likely to be in the easiest position to reduce costs because they have not been subject to stringent cost controls in the same way as older facilities. We believe these results indicate that the RPPS is fair to hospitals since it distributes Medicare payments according to patient characteristics modified by input prices and covers costs at all groups of hospitals except those who probably have high costs because they have especially high payments under the current payment system.

Given the theoretical drawbacks of the current system and the empirical inequalities in costs and outcomes, it would seem time to change the method of payment for inpatient rehabilitation cases. An RPPS would move care toward a national standard, thus improving equity across patients at the same time that it improves incentives for efficiency and improves equity across facilities.

1. INTRODUCTION

Inpatient rehabilitation is an important component of care for Medicare beneficiaries, and it has been growing rapidly. In FY 1993, Medicare paid 3.7 billion dollars for such care--a 95 percent increase from 1990 (ProPAC, 1996). This growth was on top of a 250 percent increase in the period from 1985 to 1990 (ProPAC, 1993).

Payment for inpatient care of Medicare beneficiaries given in a rehabilitation hospital, long term care hospital, or the distinct rehabilitation unit of an acute care hospital is currently made under the Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982. The payment amount depends on a per case target amount that is calculated from historical costs at the facility trended forward and on the hospital's actual cost per case. If costs are less than the target amount, then the hospital receives its costs plus an incentive payment equal to half the difference, but capped at 5 percent of the target amount. If costs are greater than the target amount, then the hospital receives its costs minus a penalty, also equal to half the difference, but total payment is capped at 110 percent of the target amount.

This payment method is quite different from Medicare's Prospective Payment System (PPS), which covers most inpatient acute care for Medicare beneficiaries. Under PPS, the amount paid for each case is based on a national formula that is essentially independent of the hospital's own costs and that adjusts for case mix using the Diagnosis Related Group (DRG) for the case.

We report here a model of a PPS for inpatient rehabilitation care of Medicare beneficiaries that is based on concepts similar to those underlying the existing PPS for Medicare acute inpatient care. Our design of the Rehabilitation PPS (RPPS) aimed to achieve three important goals: provide hospitals with incentives for efficiency, ensure access for all Medicare beneficiaries to high quality and appropriate care, and distribute Medicare payments in a way that is fair to hospitals.

If implemented, such a system could have substantial benefits compared to TEFRA. One reason for replacing TEFRA is that the variation in payment rates across facilities is unfair. Although target amounts are usually increased each year, these payments have not kept up with inflation. Because changes in case mix are not reflected in TEFRA payments, providers that have experienced an increase in the proportion of expensive cases they treat are not compensated and are thus disadvantaged. New facilities, on the other hand, have an advantage under TEFRA. During the first year of operation (two years in the case of freestanding hospitals), a new facility is exempt from TEFRA limits and this time is used to establish the facility's base cost. Consequently, the new facility receives no penalty for inefficiency during the base period and is actually rewarded for base period inefficiencies in future years. This is unfair to older providers and very likely has increased Medicare costs. In addition, it may have promoted the creation of new rehabilitation facilities and/or transfers of ownership of existing facilities, thus further increasing Medicare costs.

Table 1.1 shows that the differential treatment of new and older hospitals is not just a theoretical concern. The table shows average cost per case, target amount, and resulting incentive payments separately for the two major classes of hospitals involved in rehabilitation: freestanding rehabilitation hospitals and rehabilitation units that received an exemption from the acute care PPS. The data clearly show that target amounts and incentive payments are larger for more recently certified facilities than for those certified earlier. We expect that the decline in calculated incentive amount for hospitals in the last two years indicates the establishment of high base year costs rather than the end of the previous trend.

The theoretical concept of provider fairness that we used in the design of the RPPS is to pay each rehabilitation facility in proportion to the costs of efficiently producing the care required by its set of Medicare patients. Thus, we need to adequately account for each hospital's patient mix and for other justifiable factors that affect costs such as teaching and local wage rates. We would not want to pay hospitals for inefficiency or even for a greater intensity of care than

Table 1.1

Average per Discharge Costs, Targets, and Incentive Payments for TEFRA Rehabilitation Facilities in FY 1993-94, by Fiscal Year of Certification and Type of Facility

	Rehabilitation Hospital				Exempt Unit				Both Types			
Year Certified	N	Cost	Target	Incentive Amount	N	Cost	Target	Incentive Amount	N	Cost	Target	Incentive Amount
83	47	11071	11606	220	36	13270	12321	-161	83	12024	11916	55
84	4	27354	12357	108	226	12144	12485	28	230	12408	12483	29
85	8	10498	11994	310	72	12707	13773	46	80	12486	13595	73
86	9	13079	19866	820	75	11315	12210	52	84	11504	13030	135
87	12	11502	16640	454	52	11474	13796	387	64	11479	14329	400
88	14	14003	17511	437	57	10283	14560	548	71	11016	15142	526
89	20	13324	18960	905	58	11361	15110	559	78	11865	16097	648
90	7	15491	19301	791	50	11380	15668	679	57	11885	16114	693
91	9	13877	17690	823	38	12625	17273	684	47	12865	17353	711
92	4	18585	22819	516	47	12619	15346	576	51	13087	15932	571
93	1	11708	14390	719	7	18864	19350	92	8	17970	18730	171
all	135	12973	15509	489	718	11979	13778	250	853	12137	14052	287

SOURCE: PPS 10 Exempt Hospital and Excluded Unit Dataset, so data are for hospital fiscal years that began in federal FY 1993. Averages are hospital weighted.

is received typically by patients with similar clinical characteristics and social support level. We follow Gianfrancesco (1990) and others in using the relationship between reimbursement and costs for groups of hospitals (e.g., urban/rural, freestanding or not, etc.) as one way of detecting systematic unfairness in a payment system. A finding of a higher ratio of payment to cost in one group than another would suggest unfairness in the payment mechanism unless there was a good reason to believe that efficiency differed between the groups. Of course, some individual hospitals may have higher costs because of unmeasured patient severity or incorrectly measured input prices; if so, then a rate that is an average of a national rate and a rate based on hospital-specific historical costs would be fairer than either rate alone (Pope, 1990; Goodall, 1990). Unfortunately, determining the proper mix requires knowing the relative roles of justifiable vs. unjustifiable unobserved factors in explaining cost differences (Keeler, 1990). Insofar as the TEFRA incentive structure explains more of the variation in costs, the "optimal" mix, if we could know it, would give less weight to hospital-specific costs.

In addition to improved fairness, an RPPS would improve the cost control incentives that exist under TEFRA. Because payments would be based on national standards rather than on the hospital's own historical costs, it would provide more incentive to more-expensive providers to control costs. Research suggests that it is the more-expensive providers that reduced their costs most under the acute care PPS (Feder, Hadley, and Zuckerman, 1987; Coulam and Gaumer, 1991; Zwanziger et al., 1994). Second, TEFRA allows current costs to affect payment, and this may also provide smaller cost control incentives than PPS. To assess the potential difference in cost control incentives between an RPPS and the existing TEFRA system, it may help to realize that over half of facilities (56 percent of facilities caring for 61 percent of Medicare cases) are operating in a cost range where they would be reimbursed by TEFRA for 50 percent of a modest increase in costs while under an RPPS they would receive no extra reimbursement for most cost increases. An additional 30.4 percent of facilities (30.5 percent of cases) have costs below 90 percent of their target and thus would receive an even higher fraction of an increase in costs.

An RPPS might also provide better incentives than TEFRA to provide all beneficiaries with access and quality care. The lack of a case mix adjustment in TEFRA creates incentives for providers to specialize in relatively cheaper cases, which could conceivably limit beneficiary access. Further, TEFRA lacks outlier payments that help to mitigate PPS's incentives to underserve the most expensive patients and that provide substantial protection to providers against financial risk (Keeler, Carter, and Trude, 1988). Additional distortion of case-level payments occurs when TEFRA counts discharges that do not include a full course of rehabilitation (e.g., short stays for evaluation, cases that transfer to acute care) as full cases. These distortions may have both quality and cost control incentives.

There are, of course, drawbacks to using an RPPS. Because of the greater cost control incentives from a PPS, there will be greater incentive to discharge early, which might lead to premature discharge as well as greater use of post-hospitalization rehabilitation services such as those of Home Health Agencies (HHAs) or skilled nursing facilities (SNFs). The expected size of these effects is mitigated by the fact that hospitals already can retain some of the savings from increased efficiency under TEFRA.

Another difficulty with using a case-based PPS for rehabilitation facilities concerns the relationship between the PPS and payment for rehabilitation that occurs in other sites--particularly in SNFs and HHAs. There is some overlap in the populations seen in these sites (Kramer et al., 1997), and using different payment systems in different sites may lead to inappropriate sorting of patients leading to undesirable clinical and fiscal consequences. Unfortunately, pursuing this issue was beyond the scope of the research covered here.

CASE CLASSIFICATION AND UNIT OF PAYMENT FOR AN RPPS

One of the reasons for the initial exclusion of rehabilitation hospitals from the PPS was that DRGs could not predict resource use at these facilities very well. Functional status, measured by activities of daily living and mobility, is much more correlated than diagnoses with charges for the patient (Hosek et al., 1986). Restoring functional status is the goal of rehabilitation and thus functional status at admission is one of the primary determinants of resource use.

Recently Margaret Stineman and colleagues developed Function Related Groups (FRGs) based on the Functional Independence Measure (FIM^{SM}) as well as on a clinically derived set of rehabilitation impairment categories (RICs) (Stineman, Escarce, et al., 1995). The FIM is an 18-item measure covering six domains: self-care, sphincter control, mobility, locomotion, communication, and social cognition (Stineman, Hamilton, et al., 1994).

In a companion report, Carter et al. (1997) evaluated the FIM-FRGs and found that FIM-FRGs use the right organizing concepts for a rehabilitation patient classification system--impairment groups subdivided by functional status and age. The study found further that they are good predictors of resource use. The analysis suggests that the FIM-FRGs could be a suitable basis for an RPPS, but that certain modifications would produce even better groups for payment purposes.

We use the method developed in Carter et al. (1997) to create FRGs based on the all-payer Uniform Data Set for medical rehabilitation (UDSmr^{SM}) population of cases as the basis of the model RPPS developed in this report. The modification introduces changes in the definition of the FRGs to account for more recent data and changes the stopping algorithm to limit the number of categories in the classification system. More important, it expands the number of categories by paying each FRG according to whether the case had certain comorbidities. There are approximately five FRGs per RIC for a total of 82 FRGs.

Although this classification system uses the most important reliably measured determinants of resource use--RIC, functional status, cognitive status, age, and comorbidity--it does not control for all individual factors affecting resource use. Other factors that probably affect resources include level of impairment and a variety of psychological and social factors. It is important to note that practicality limits the number of categories that can be used for payment and that one would expect that most of these effects will average out across the cases at a hospital. An important exception is that hospitals that treat a high percentage of poor patients may experience higher costs. The payment system will deal with this in a different way, as we will explain later.

The FIM is calculated from data in the UDSmr. The UDSmr database treats cases transferred from rehabilitation to acute care for 30 days or less as a single, interrupted, rehabilitation case while current HCFA rules count each part of the interrupted case as separate rehabilitation discharges if the case is actually discharged from the rehabilitation facility (which it often is). Thus, we could build a prospective payment system where the unit of payment is either the UDSmr case or the Medicare discharge. We construct RPPSs using both definitions to show that the difference is very small.

When the Medicare discharge is used as a unit of payment, we pay separately for each part of an interrupted stay. Therefore, we split the FRGs only on the presence of comorbidities and use 164 (= 82*2) FRGC payment rates. When the UDSmr case is the unit of payment, we split the FRGs on both the presence of comorbidities and whether or not the case was interrupted, and therefore use 328 (= 82*4) FRGCI payment rates.

SCOPE OF PAYMENT IN THE MODEL RPPS

In addition to unit of payment and case classification system, scope is an important issue in the design of the RPPS. Currently, hospital inpatient rehabilitation care is delivered to Medicare beneficiaries in four kinds of hospitals: (1) freestanding hospitals that received exemption from the PPS as rehabilitation facilities and are identified because the third and fourth digit of their Medicare provider number is '30'; (2) acute care hospitals with exempt rehabilitation units identified either by the existence of a rehabilitation subprovider on the Exempt Hospital and Excluded Unit Data cost report or by a majority of their rehabilitation cases (cases either assigned to DRG 462 or cared for in an exempt unit--i.e., with a provider code of T) being shown on the Medicare records as being cared for in an exempt unit; (3) other freestanding hospitals, primarily long-term care hospitals (third and fourth digit of their Medicare provider number is '20'); and (4) other acute care hospitals, including acute care hospitals in Maryland as well as PPS hospitals. As discussed further in Section 2 below, we designed the model RPPS on the first three categories.

PAYMENT ELEMENTS

The payment for case j in hospital i in classification group k under an RPPS would be calculated as follows:

$$P = R^{*}A_i{*}W_k + Z_j,$$

where R is the national payment rate, A_i is the facility's payment factor, and W_k is the FRGC (or FRGCI) weight, and Z_j is a patient-specific adjustment to account for unusual cases such as outliers.

This report evaluates options for these payment elements of the RPPS with the intent of providing strong cost containment incentives while ensuring that the payment system does not hinder beneficiary access, is fair to providers, and does not present large opportunities for profit from gaming. Elements include an algorithm for calculating relative weights, facility-level payment factors, payment adjustments for unusual cases such as low cost cases, transfers, and outliers, and an algorithm for calculating a budget neutral payment rate from available data.

Another important issue is the design of a monitoring and evaluation system for the new PPS. The change in FIM between admission and discharge might be used to monitor hospitals to protect against the PPS incentive to discharge patients too early. Similarly, the proportion of patients residing in a SNF for a short period after discharge--say 30 days--might be an indicator that a hospital may be discharging patients too early.

OVERVIEW OF REPORT

Section 2 of this report describes our data and gives the definition of the primary variables used in our analyses. Sections 3 through 5 cover the elements of an RPPS: weights, facility-level adjustments, and patient-level adjustments, respectively. There are options for several of these elements. The pros and cons of alternatives and supporting analyses are presented in each case.

A simulation program was used to examine the joint performance of all the elements. These simulations assume no behavioral response by hospitals to the RPPS. The simulation methods and results are presented in Section 6. Section 7 describes possible methods of monitoring outcomes of an RPPS and Section 8 presents the conclusions of our analyses.

2. DATA AND VARIABLE DEFINITIONS

DATA

Two data systems are the primary sources for our analyses: the Uniform Data System for medical rehabilitation (UDSmr^{SM}) and Medicare program information. The UDSmr records functional status and demographic information about rehabilitation patients in participating hospitals. The Medicare data files include discharge files recording demographic and financial information and hospital-level files providing facility characteristics and financial information. We describe these two data sources further below.

Our analyses were based on a set of calendar year 1994 cases from the UDSmr that were matched to the Medicare Provider Analysis and Review (MEDPAR) file. The matching process and its results are discussed in Carter et al. (1997). The match rate was quite high: Ninety-four percent of the UDSmr discharges with Medicare as the primary payer were matched to MEDPAR records. The percentage of MEDPAR discharges for which a UDSmr record was found varied by hospital, but 78 percent of hospitals with a full year of UDSmr data had a match rate exceeding 80 percent.

UDSmr

The UDSmr file describes rehabilitation stays in participating hospitals. The data include demographic descriptions of the patient (birth date, gender, zip code, ethnicity, marital status, living setting), clinical descriptions of the patient (condition requiring rehabilitation, ICD-9-CM diagnoses, FIM at admission, FIM at discharge), and the hospitalization (hospital, admission date, discharge date, charges, payment source, and an indicator of whether this was the first rehabilitation hospitalization for this condition, a readmission, or a short stay for evaluation). The UDSmr system also contains follow-up information providing, for some cases, the FIM and living setting at a time following discharge, although we did not use these follow-up data. UDSmr is operated within the Center for Functional Assessment Research under the Department of Rehabilitation Medicine of the School of Medicine of the State University of New York at Buffalo, as a division of the University of Buffalo Foundation Activities, Inc.

The number of hospitals participating in the UDSmr has been growing rapidly--from 342 at the end of 1993 to 410 in 1994 and 472 in 1995. The hospitals cover 48 of the 50 states and provided UDSmr with good data on 192,838 first admissions in 1995 (Fiedler and Granger, 1997).

We used UDSmr data from calendar year 1994. UDSmr provided us with data on 139,360 cases from 352 inpatient hospital facilities that agreed to have their data used in this study. (Because some UDSmr facilities did not wish to participate, these numbers are lower than those reported by UDSmr.) Some of these cases are what are known as "interrupted stays," which occur when the patient's rehabilitation treatment is interrupted by an acute care hospitalization and the person returns to the same rehabilitation facility within 30 days after leaving it. Typically, Medicare counts an interrupted stay with a single acute care hospitalization as two rehabilitation discharges, one with two acute care hospitalizations as three rehabilitation discharges, etc. We will confine our use of the word "discharge" to that used by Medicare and use the word "case" to cover the UDSmr unit. Using these rules, the 139,360 cases correspond to 144,719 discharges. Interrupted stays constitute about 3.1 percent of UDSmr cases and 6.4 percent of Medicare discharges.

The UDSmr record contains the dates of transfer to and return from acute care, for up to three acute care hospitalizations. We used this information to expand the UDSmr case records into the corresponding discharges. Note this means that, for the second and later discharges within interrupted stays, our data on the FIM at admission do not correspond to admission for the discharge, but rather to admission for the case. Consequently, throughout the study, we analyze data both by the case and by the discharge. We found only small differences and, consequently, believe that this problem has not had a large effect on our results.

UDSmr provides training to participant hospitals and provides examinations that certify the data (Fiedler and Granger, 1997). Until a facility passes the certification exam, the data are not considered adequate and were excluded from our data file. Since hospitals continue to join the UDSmr, we have only partial-year data from 59 of the 352 hospitals.[1] The data are also routinely screened for out-of-range values and returned for correction. Our frequencies confirmed the accuracy and completeness of this screen. The success of our match to Medicare discharge records testifies further to the accuracy of the demographic information on the UDSmr. Unfortunately, diagnosis codes are not included in this screen and frequently are invalid values.

Our matched dataset contains 100,080 discharges from 350 hospitals. It excludes 299 discharges without positive MEDPAR charges and 365 additional discharges with incomplete data.[2] Because some of the discharges are multiple parts of an interrupted stay, the matched discharges correspond to 96,772 original UDSmr cases.

As shown in Carter et al. (1997), the set of UDSmr hospitals overrepresents freestanding rehabilitation hospitals and underrepresents exempt units of acute care hospitals. Table 2.1 shows that our set of matched cases has the same properties. The table shows the subtotal excluding acute care hospitals without an exempt rehabilitation unit because that is the sample that we used in this report. Carter et al. provide a detailed comparison of the Medicare population and the

Table 2.1

Comparison of Number of Sample Discharges with All Medicare Rehabilitation Cases, by Type of Hospital

Type of Hospital	Sample	All Medicare	Percent in Sample
Freestanding rehabilitation	46,649	103,166	45.2
Exempt unit of acute care hospital	49,018	202,471	24.2
Long-term care	3,435	5,201	66.0
Subtotal	(99,102)	(311,755)	31.8
Other acute care hospital	978	6,118	16.0
Total	100,080	316,956	31.6

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[1] For 4 of the 59 hospitals the UDSmr data exclude the end part of the year. We are not sure why these hospitals stopped sending data to UDSmr, but some may have failed UDSmr's periodic recertification.

[2] This count includes discharges where other parts of the UDSmr case were not available.

Medicare cases in the UDSmr. They find that the matched sample is generally representative of all Medicare beneficiaries and of disabled beneficiaries on such demographics as age, ethnicity, and Supplemental Security Income (SSI) status.

Medicare Data

We used three Medicare data files. The MEDPAR file describes all inpatient stays (including rehabilitation stays) paid for by Medicare, and the Health Care Provider Cost Report Information System (HCRIS) provides hospital information at the hospital and exempt unit level. Information about post-rehabilitation care was obtained from a post-acute care file constructed from the Standard Analytic Files (SAF) for purposes of internal Health Care Financing Administration (HCFA) analyses.

The MEDPAR file contains one record for each discharge that is paid by Medicare, including discharges from rehabilitation facilities. We used the 1994 calendar year MEDPAR, which matches the time period of our UDSmr data. The data include patient demographics (age, gender, race, zip code of residence), clinical characteristics (diagnoses and procedures), and hospitalization characteristics (admission date, discharge date, days in intensive care, charges by department, and reimbursement information).

For the purposes of the tables in this section, we defined a rehabilitation discharge on the MEDPAR as any case that meets at least one of the following criteria: (1) a discharge from a freestanding rehabilitation hospital or exempt rehabilitation unit, (2) a discharge assigned to DRG 462 in either acute care hospitals or long-term care (LTC) hospitals, and (3) any discharge in an LTC facility that matched a UDSmr case. We use the term rehabilitation facility to refer to all the facilities that engage in inpatient rehabilitation--including freestanding rehabilitation hospitals, excluded units, and LTC hospitals. The data in subsequent sections are restricted to our sample of matched UDSmr and MEDPAR records.

Hospital cost reports are contained in the HCRIS. The cost report files contain information on facility characteristics, utilization data, and cost and charge data by cost center. Each record covers a hospital fiscal year, and all the records that cover hospital fiscal years that began during a specific federal fiscal year are kept together in the same file. The file is named according to the number of years from the beginning of the acute care PPS. We used the latest available files--PPS 10 files (i.e., hospital fiscal years that began during the period from 10/1/92 through 9/30/93). Thus, the cost report data cover a somewhat earlier time period than the MEDPAR data, with the time difference varying by provider--from 15 months (for hospitals whose fiscal year begins on October 1) to, typically, 6 months (for hospitals whose fiscal year begins July 1).

We took hospital location, year of certification, and cost-to-charge ratios from the Exempt Hospital and Excluded Unit Dataset, supplemented by data from the PPS 10 Hospital Minimum Data Set for hospitals in Maryland, those not exempt from the acute care PPS, and 16 facilities missing an exempt record. The type of residency programs available at hospitals with exempt units was determined from the American Medical Association's (AMA's) Directory of Graduate Medical Education programs.

We prepared a list of all MEDPAR records in our matched sample containing the Health Insurance Claim (HIC) number, provider number, admission, and discharge dates. HCFA provided us with SAF records for inpatient, SNF, and HHA records during 1994 and the first month of 1995 for any beneficiary appearing on this list. We used these data to determine the use of SNF and HHA in the 30 days following rehabilitation. Unfortunately, for reasons that are not apparent, we did not receive records for almost 5 percent of our discharges (we should have received the record of the rehabilitation stay even if the patient used no other care). An examination of the missing cases showed no pattern related to time frame or rehabilitation provider, and we assumed the missing data were random in the illustrative calculation in Section 7 that is our only use of these records.

Resource Use in Sample

Table 2.2 shows several measures of resource use for all MEDPAR rehabilitation discharges. Freestanding hospitals exempt from the PPS for reasons other than rehabilitation (predominantly long-term care

Table 2.2

Resource Use for Medicare Rehabilitation Discharges, by Type of Hospital

Type of Hospital	Avg. LOS	Avg. Charges	Avg. Daily Therapy Charges	Number of Cases
Freestanding rehabilitation	19.9	21,508	343	103,166
Exempt unit of acute care hospital	17.1	17,929	299	202,471
Other freestanding hospital	25.3	23,836	256	5,201
Maryland acute care hospital	15.6	11,992	229	2,767
Other acute care hospital	12.4	11,081	319	3,351
Total	18.1	19,066	312	316,956

SOURCE: Calculated from MEDPAR file.

hospitals but also including a few specialty hospitals) have substantially longer average length of stay (LOS) than typical rehabilitation facilities (in lines 1 and 2 of the table) while acute care hospitals outside of Maryland have substantially shorter LOS. Non-exempt acute care hospitals have substantially lower costs per rehabilitation case than rehabilitation facilities. Because of their long LOS, long-term care hospitals actually cost more than rehabilitation facilities, but provide less therapy each day (as measured by charges). Table 2.3 provides similar information for our matched sample.[3] Although UDSmr nonrehabilitation facilities are more like rehabilitation facilities, the general pattern is similar: the small number of acute care cases use the least resources and the long-term care hospitals have longer LOS than average.

We compared a variety of UDSmr fields across types of facilities and found differences in demographics to be quite modest, although cases in acute care hospitals are slightly younger than other rehabilitation cases. Although there were differences in the distribution of Rehabilitation Impairment Categories, these should not be of concern because the case classification system should be able to adjust for these differences.

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[3] These data include the 365 discharges that were subsequently eliminated from our analysis file because of incomplete data.

Table 2.3

Resource Use for Medicare-UDSmr^{SM} Sample Discharges, by Type of Hospital

Type of Hospital	Avg. LOS	Avg. Cost	Avg. Charges	Avg. Daily Therapy Charges	Number of Discharges
Stand-alone rehabilitation	19.96	13,800	21,223	333	46,874
Exempt unit of acute care hospital	17.33	12,296	17,231	311	49,026
Other stand-alone hospital	23.18	14,485	20,072	256	3,590
Maryland acute care hospital	18.06	13,150	15,074	246	894
Other acute care hospital	16.36	10,108	13,542	216	84
Total	18.8	13,082	19,173	318	100,468

SOURCE: Calculated from MEDPAR data on matched sample.

HOSPITAL UNIVERSE

We excluded PPS acute care rehabilitation cases from the rehabilitation PPS, in part based on the preceding analyses. These cases use substantially fewer resources than more typical rehabilitation cases. There are so few cases in our matched sample that we did not believe that we could adequately test whether our rehabilitation PPS could adequately measure case-mix differences. We also excluded hospitals in Maryland. Maryland hospitals have a Medicare waiver and are not paid under PPS; instead, their payments are negotiated with the state rate commission. Because these hospitals are not operating under TEFRA, they are subject to different incentives and we do not expect their current behavior to be similar to that of the hospitals that would be paid under an RPPS.

The long-term care TEFRA hospitals are included in the RPPS. Many of these hospitals care for a lot of cases that are very similar to the cases found in rehabilitation facilities--indeed, the cases in the UDSmr matched dataset are clearly viewed as rehabilitation cases by the hospitals and most appropriately paid using the same system as TEFRA rehabilitation facilities.

Many of these long-term care hospitals, however, also care for a subset of patients that are different from almost all of those in rehabilitation facilities. We reached this conclusion based on analyses of use of therapists and principal diagnoses at hospitals that participate in the UDSmr. It appears that most (but not all) of the LTC facilities participating in the UDSmr selectively send cases to UDSmr. Twenty-two percent of MEDPAR cases at the UDSmr LTC hospitals that were not sent to UDSmr receive minimal therapy (charges less than $10 per day), compared to less than one-half of one percent of UDSmr cases at the same hospitals. See Table 2.4. Fifty-six percent (= 21.5 + 34.5) of unmatched cases spend less than $159 per day on therapy which is the 25th percentile of all cases at these hospitals.

The cases not sent to UDSmr are more likely than the UDSmr cases to have primary diagnoses related to the respiratory system, disorders of the skin, psychiatric disorders, or alcohol/substance abuse. See Table 2.5 for MEDPAR cases at UDSmr long-term care hospitals, by major diagnostic category (MDC) and match status. These categories constitute about half of the unmatched MEDPAR cases at these hospitals. The other half of the unmatched MEDPAR cases have diagnoses that largely fall into rehab categories (stroke, lower extremity fracture, rehabilitation) and a resource use profile roughly similar to the UDSmr cases (details not shown).

Table 2.4

Distribution of Therapy Charges, by Match Status for LTC Hospitals Participating in UDSmr

	Percent of Cases		
Daily Therapy Charges	Unmatched	Matched	Total
0 - 10	21.5	0.4	7.4
10 - 159	34.5	9.4	17.6
159 - 235	22.1	26.6	25.2
235 - 287	12.6	30.9	24.9
> 287	9.4	32.6	25.0
Total	100	100	100

NOTE: Based on 1736 unmatched and 3567 matched cases at 12 LTC hospitals; excludes one LTC hospital that joined UDSmr very late in the year and sent only 14 (out of 987) cases and three months of another hospital that participated in UDSmr for only nine months.

Table 2.5

MEDPAR Cases at UDSmr Long-Term Care Hospitals, by MDC and Match Status

MDC	Number of Cases Unmatched	Matched	% Matched
1. Nervous system	355	1047	75
4. Respiratory system	459	71	13
8. Musculoskeletal and connective tissue	284	846	75
9. Skin, subcutaneous tissue and breast	67	9	12
19. Mental diseases and disorders	281	4	1
20. Alcohol/drug use and induced mental disorders	64	0	0
23. Factors including rehabilitation	74	1474	95
All others	159	126	44
Total	1743	3577	67

To summarize the data in Table 2.5 in another way: approximately 80 percent of all cases at the LTC hospitals participating in UDSmr are probably rehabilitation cases similar to those at other rehabilitation facilities.[4] This 80 percent includes all the matched cases and the unmatched cases in MDCs 1, 8, and 23. Most of the remaining 20 percent of cases can be clinically grouped. It would be feasible to extend the RPPS payments to these cases after grouping based solely on clinical characteristics. Alternatively, one could pay for these nonrehabilitation cases using the methodology developed for nonrehabilitation SNF cases.

Because of resource constraints, we were not able to extend the development of the RPPS to nonrehabilitation cases. However, because it is important to treat similar rehabilitation cases in all sites equally, we did include the matched UDSmr cases from LTC hospitals in all our analyses. The analyses will shed light on the extent to which an RPPS would adequately compensate these hospitals for their rehabilitation cases.

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[4] We can get a lower bound of 72 on the percentage of rehabilitation cases by assuming that the unmatched cases with charges for daily therapy greater than the median amount for the matched cases were rehabilitation cases. This is a lower bound because it counts as rehabilitation only cases that had as much therapy as the most intensive half of the cases known to be rehabilitation. If, instead, we picked a sample of unmatched cases that matched the distribution of daily therapy charges of the matched cases, we would get an unbiased estimate that 77 percent of cases at these LTC hospitals are in rehabilitation that we evaluate as close to the 80 percent from the clinical analyses.

VARIABLE DEFINITIONS

We next describe the variables that underlie our analyses. Subsequent sections describe how these variables are used to construct the variables describing payment elements: relative weights in Section 3, facility level payment adjuster in Section 4, and patient-level adjustments in Section 5.

FIM Score

The Functional Independence Measure (FIM) is an 18-item measure covering six domains: self-care (six activities of daily living), sphincter control (two items on bowel and bladder management), mobility (three transfer items), locomotion (two items on walking/wheel chair use and stairs), communication (two items on comprehension and expression), and social cognition (three items on social interaction, problem solving, and memory). All 18 items are scored into one of seven levels of function ranging from complete dependence (1) to complete independence (7). The scores are summed to produce the total FIM score. The first four domains--self-care, sphincter control, mobility, and locomotion--are combined into a single motor scale, and the last two domains--communication and social cognition--are combined to form a single cognitive scale. The FIM was developed for inpatient rehabilitation cases (B. B. Hamilton et al., 1987).

Rehabilitation Impairment Category (RIC)

Using the FIM, a team of researchers from the University of Pennsylvania developed a patient classification system, Function Related Groups, referred to as the FIM-FRGs (Stineman et al, 1986). The FIM-FRGs are organized around 20 Rehabilitation Impairment Categories (RICs) which are defined clinically from the cause of impairment. These categories are shown in Table 2.6.

Table 2.6

Rehabilitation Impairment Categories

RIC	Name
01	Stroke
02	Brain dysfunction, traumatic
03	Brain dysfunction, nontraumatic
04	Spinal cord dysfunction, traumatic
05	Spinal cord dysfunction, nontraumatic
06	Neurological conditions
07	Orthopedic--lower extremity fracture
08	Orthopedic--lower extremity joint replacement
09	Orthopedic--other
10	Amputation, lower extremity
11	Amputation, other
12	Osteoarthritis
13	Rheumatoid and other arthritis
14	Cardiac
15	Pulmonary
16	Pain syndrome
17	Major multiple trauma, without injury to brain or spinal cord
18	Other disabling impairments
19	Guillain-Barré
20	Major multiple trauma, with injury to brain or spinal cord

FRG, FRGC, and FRGCI

RICs are subdivided into FRGs using a recursive partitioning algorithm that groups patients with similar lengths of stay based on age, FIM motor score, and FIM cognitive score. The FRGs that we use are defined in Carter et al. (1997) with the same definitions used to group either MEDPAR discharges or UDSmr cases. FRGs containing MEDPAR discharges are subdivided into FRGCs based on the presence or absence of at least one of a defined set of comorbidities. (See Carter et al., 1997, for definition of comorbidity set.) FRGs containing UDSmr cases are subdivided into FRGCIs based on the combination of the presence or absence of a comorbidity and the status of the case as an interrupted stay or not.

Cost

The cost for each sample case was calculated using the departmental cost-to-charge ratio (CCR) method (Newhouse et al., 1989). Because some departmental CCRs were beyond plausibility, values were trimmed to plus or minus three standard deviations of the mean. Separate limits were applied for stand-alone hospitals and for units. Cost reports were missing for seven of the 350 hospitals, and median CCRs (within type of hospital) were used to calculate their costs.

Teaching

Measuring teaching intensity at rehabilitation facilities is not as straightforward as one would like. The preferred variable is analogous to that used for indirect medical education (IME) payments under the capital PPS--the ratio of residents to average daily census. For hospital fiscal years that began after July 1, 1991, the count of residents for the numerator is a full-time equivalent (FTE) determined by apportioning residents based on the amount of time spent in the portion of the facility that is under PPS or in the outpatient department. This number is similar to, but not identical with, the FTE count used for payment of the direct cost of graduate medical education (GME) payments. The GME FTE count includes residents who spend time in excluded facilities and certain ambulatory settings, but downweights residents who have finished the initial part of their residency.

For rehabilitation facilities, we would want the numerator to equal the number of FTE working in the rehabilitation department. For freestanding rehabilitation hospitals, the net full-time interns and residents from the minimum dataset is a reasonable proxy. For excluded units, the difference between the facility total and the hospital total was apportioned among the subproviders defined in HCRIS in proportion to the size of the residency program in the related specialty as given by the AMA's *Directory of Graduate Medical Education*. The directory information on number of physical medicine and rehabilitation residents and on psychiatric residencies is inexact because of residencies that are shared across multiple hospitals. Consequently, we supplemented this information with telephone calls to individual facilities. In most such cases, the possible discrepancies are quite small because there are only a few interns and residents outside the acute care hospital. We called hospitals in the handful of cases where there were more than 10 ambiguous slots to be allocated. It was somewhat gratifying that the correct answer in each case was quite close to the number that we would have allocated using the proportionality rule. There were too few hospitals for this to be a real validation of the formula. We also called several freestanding facilities that looked like outliers in our regression and found that their cost report data were in error. Despite our efforts, it remains possible that errors still remain in our teaching measure for some hospitals.

Wage Index

We retrieved wage indices from the file used to standardize DRG weights for the FY 1997 "Notice of Proposed Rule Making" (DHSS, 1996, p. 27453). Since the data were from PPS 10, they cover hospital fiscal years that began from October 1992 through Sept 1993 and are roughly contemporaneous with our CY 1994 discharge abstracts. Values for exempt hospitals were obtained by matching on Metropolitan Statistical Area (MSA), as these facilities do not appear in the file.

Low Income Population

We used the UDSmr data from our matched sample to calculate the fraction of Medicare cases at each hospital for which Medicaid was listed as a payer. In almost all cases, Medicaid was listed as secondary payer, but it was listed as primary in some cases.

Time Period of Certification

We use the time period of certification as a surrogate for the amount of pressure that TEFRA has put on the facility to contain costs. As discussed in the Introduction, newer facilities are subject to much lower pressure than older facilities. A better measure of amount of pressure might be constructed if we had data on TEFRA payments that were contemporaneous with our discharge data--i.e., exempt facility data from PPS 11 and 12.[5] These data are not available.

The exempt hospital cost report lists the date of certification as an exempt facility (fields E12 through E16). For analysis purposes, we grouped hospitals into three groups: those certified in FY 1984 or earlier, FY 1985 through 1989, and those certified in 1990 or later.

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[5] For example, Feder, Hadley, and Zuckerman (1987) defined an index of the relative pressure under PPS from costs and PPS payment amounts.

Exempt hospital cost reports were missing for 15 rehabilitation facilities (4.4 percent). We counted these facilities among the recently certified group. We checked that the minimum dataset for PPS 10 showed no exempt unit for the acute hospital and that freestanding providers had Medicare provider numbers higher than those of other freestanding hospitals.[6] In preliminary analyses we found them statistically indistinguishable from other recently certified providers.

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[6] Medicare numbers are often but not always assigned sequentially, and thus we view this as additional evidence in favor of the proposition that these hospitals were certified after the close of PPS 10.

3. RELATIVE WEIGHTS

As shown in the Introduction, for any particular hospital, the payment for each case is proportional to the relative weight assigned to the patient's FRGC (or FRGCI). To ensure that beneficiaries in all FRGCs will have access to care and to encourage efficiency, we set the weights to be proportional to the resources needed by a typical case in the FRGC. So, for example, cases in an FRGC with weight of 2 will cost twice as much as cases in an FRGC with a weight of 1.

The average of the relative weights for a set of cases is called the case mix index or CMI. The CMIs for cases at different hospitals can be compared to describe the relative costliness of each hospital's case mix.

There are a variety of alternative ways in which relative weights could be calculated. Alternatives differ in the classification system that is the basis of payment, the measure of resource use, the method used to control for variations in costs across facilities, and whether the weight algorithm should account for the proportion of outlier payments in the payment group. We selected several of these for analysis. An overview of these alternatives is given below along with the reason for selecting them. Then we provide the mathematical specification of the alternative ways of controlling for hospital costs. In Section 4, we will examine the effectiveness of each of the alternatives in explaining costs at the hospital level.

ALTERNATIVES FOR EVALUATION

Table 3.1 lists the alternative weights we evaluated. As discussed earlier, the UDSmr treats cases transferred from rehabilitation to acute care for 30 days or less as a single, interrupted, rehabilitation case while current Medicare rules count each part of the interrupted case as a separate rehabilitation discharge if the case is actually discharged from the rehabilitation facility (which it often is). We took charge-based weights using the MEDPAR discharge as the unit of payment as the most likely set of weights. Thus, we calculated only one set of weights

Table 3.1

Weight Methods to Be Evaluated

Name of Weight	Unit of Payment	Resource Measure	Control for Hospital Cost	Control for Outlier Payment
Standard	MEDPAR discharge	Charge	Payment factor	No
UDSmr case	UDSmr case	Charge	Payment factor	No
Cost weights	MEDPAR discharge	Cost	Payment factor	No
HSRV	MEDPAR discharge	Charge	Hospital specific	No
Fair weights	MEDPAR discharge	Charge	Payment factor	Yes

where the unit of payment is the UDSmr case and several based on the MEDPAR discharge.

Resource Measure

Cost-based weights were used in the initial acute care PPS implementation, but charge-based weights have been used since FY 1996. Cotterill et al. (1986) found charge- and cost-based weights for the acute care PPS to be quite similar. Charge-based weights can be updated more quickly than cost-based weights because they do not require the filing and auditing of cost reports, a process that may take up to two years. Charge-based weights can be updated based on discharge data that are typically available after only six months.

The intensity of rehabilitation care delivered during each day is more homogeneous than is acute care, with the great majority of expenses involving only a few cost centers (routine care, physical therapy, and occupational therapy) and less variation across cases in the mix of ancillary and routine care. Thus, we expect that FRGC (or FRGCI) charge-based weights would be more similar to cost-based weights than are DRG charge-based weights to cost-based weights. Consequently, we calculated several variations in charge-based weights, but only a single cost-based weight to verify that it was indeed similar to the analogous charge-based weight.

Controlling for Hospital Costs

Both charges and costs are affected by hospital characteristics for which the RPPS would adjust payment--i.e., the factors that go into the calculation of the facility payment factor (A_i in the payment formula in the Introduction). In the standard method used to calculate DRG weights, charges are first standardized by the factors used to pay operating costs associated with teaching, disproportionate share, and input prices. The payment factors capture only a small part of the variation across hospitals in charges for any specific DRG.

A method that would account for more of the cross-hospital variation in charges than the standard method is the hospital specific relative value (HSRV) method. The HSRV method differs from the standard method in that a hospital's charges are not standardized using its payment factor, but instead are standardized using hospital-specific charges and the hospital's case mix index. If, within each hospital, charges were set in proportion to costs, then the HSRV method would clearly be superior to the standard method to the extent it produces weights that reflect relative costs. However, because pricing rules vary and are unknown, there is no guarantee that, after averaging across hospitals, the HSRV method will yield relative weights closer to relative costs.

We evaluated both methods of controlling for hospital costs. Using the standard method and the facility payment factor to standardize charges provides similarity to the acute care PPS. However, Hosek et al. (1986) found substantial correlation in charges and length of stay for patients treated at the same facility even after controlling for impairment group, functional status, and facility characteristics. Further, the TEFRA rules have allowed newly certified units to recover larger costs. Thus, there is *a priori* reason to believe that there is substantial variation across hospitals in costs that might be better controlled by the HSRV method.

Fair Weights

Outlier payments will be a higher percentage of RPPS payments in some FRGs than in others. This is appropriate insofar as it provides more outlier payment for the cases that would otherwise cause the highest losses. Under the acute care PPS, DRG weights are proportional to the resources used by the average case in the DRG. An alternative would be to calculate weights so that total PPS standardized reimbursement (including outlier payment) would be proportional to the resources used by the average case in the DRG. Such "fair weights" are under consideration by ProPAC (1994). Adjusting for the amount of outlier payment received by cases in each FRG makes intellectual sense but might have only a modest effect on total payment and could add substantial administrative complications. To examine the effect of fair weights, we modified the standard method charge-based weights to account for outlier payments.

Summary of Alternatives

Table 3.1 summarizes the calculated and evaluated alternative weights. We took as the most likely set of weights those that are most similar to the acute care PPS, viz., charge-based weights using the MEDPAR discharge as the unit of payment, the payment factor to control for hospital costs, and no control for outlier payments. Next, we provide details about the algorithms used to calculate these weights.

ALGORITHM

In calculating weights, we eliminated transfer cases that stayed less than the arithmetic mean length of stay (LOS) for their FRG, since such cases will not receive the full payment amount.[1] In the acute care PPS, HCFA currently uses such cases, but weights them according to the portion of the DRG payment they will receive. It would be possible to do this when RPPS weights are recalibrated, but we needed the weights before we could analyze payment amounts for transfer cases.

Overview of Weight Algorithms

As shown in Carter et al. (1997), the presence of comorbidities or an interrupted stay multiplies the expected resource use of a case by the same amount for each FRG in the same RIC. This relationship was found empirically to produce a good fit. For example, we tested whether comorbidities had different effects in different FRGs within the same RIC and found that they did not. We used residual plots to show that the multiplicative model fit the data (rather than, for example, an additive model).

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[1] These omitted short stay transfers comprise 4 percent of UDSmr cases and 6.6 percent of MEDPAR discharges.

Because of the multiplicative model, the first step in the calculation of FRGC weights is to estimate the effect of comorbidity. The second step is to adjust the charges (or costs) of each discharge (or case) for these effects. These adjusted resource use values for each discharge (or case) are then used to calculate "relative adjusted weights" in each FRG. Different algorithms are used for the standard method, the HSRV method, and for fair weights. The final steps are to calculate the weight by modifying the "relative adjusted weight" with the effects of comorbidity (and interrupted stays) and normalize the weights to 1.

Effect of Comorbidity and Interrupted Stay

For FRGCI weights using the UDSmr case as unit of payment, the effect of interrupted stay is calculated simultaneously with the effect of a comorbidity.

We define the indicators:

x = 1 if the patient had one or more comorbidities,
  = 0 otherwise, and
y = 1 if the patient had an interrupted stay,
  = 0 otherwise.

Then, the weight for a UDSmr case in FRG k will be given by

$$W(k,x,y) = \exp(ax + by)*w_k, \tag{1}$$

where a and b come from a regression of log of charge on x, y, and dummy variables for each FRG in the RIC and w_k is the "adjusted weight" for the FRG. The first six columns of Table 3.2 show data for regressions on the log of charge per UDSmr case in each RIC. It includes the coefficients a and b, as well as their t-statistics and the R-square and sample sizes for the regression.

Table 3.2

Charge Data: Coefficients for Interrupted Stay and Comorbidity from Regressions of Log of Charge per Case, Controlling for FRG and Coefficients for Comorbidity from Regressions of Log of Charge per Discharge Controlling for FRG

		Charge per UDSmr Case					Charge per MEDPAR Discharge			
		Interruption		Comorbidity		Sample		Comorbidity		Sample
RIC	R-Square	coef.	t-stat	coef.	t-stat	Size	R-Square	coef.	t-stat	Size
1	0.23	0.3378	19.68	0.0000	NA	28,775	--	--	--	30,108
2	0.20	0.5978	7.25	0.0949	1.87	1,142	0.14	0.0404	0.80	1,215
3	0.21	0.4281	6.69	0.0780	2.50	1,946	0.17	0.0875	2.85	2,063
4	0.15	0.3339	2.52	0.0098	0.14	629	0.11	0.0483	0.69	677
5	0.30	0.4770	8.19	0.2215	6.30	2,556	0.24	0.1911	5.53	2,699
6	0.14	0.5666	10.54	0.1015	3.92	4,075	0.10	0.1067	4.20	4,230
7	0.14	0.4040	14.58	0.1214	8.43	13,909	0.11	0.1020	7.18	14,375
8	0.19	0.4343	14.54	0.2007	13.44	17,280	0.16	0.1917	13.04	17,658
9	0.10	0.5669	10.39	0.1584	5.19	3,934	0.06	0.1373	4.58	4,067
10	0.14	0.4875	4.63	0.0571	1.08	1,223	0.11	0.0549	1.07	1,261
11	0.14	0.3906	3.37	0.2509	5.08	1,295	0.13	0.2359	4.83	1,336
12	0.14	0.6261	14.47	0.0405	1.67	3,557	0.08	0.0390	1.64	3,789
13	0.16	0.7791	4.79	0.0157	0.18	262	0.06	0.0189	0.22	284
14	0.28	0.4337	7.60	0.1464	5.23	2,269	0.24	0.1440	5.24	2,366
15	0.14	0.4162	5.38	0.0663	2.04	1,834	0.11	0.0566	1.73	1,905
16	0.06	0.6063	4.13	0.1772	2.53	1,206	0.05	0.1510	2.20	1,207
17	0.16	0.2325	1.37	0.2383	2.66	330	0.12	0.2258	2.52	351
18	0.17	0.5299	12.80	0.1024	5.62	4,986	0.13	0.0960	5.24	5,236
19	0.31	0.2400	1.49	0.0972	0.85	232	0.24	0.0174	0.15	250
20	0.36	0.0222	0.07	0.2101	1.35	117	0.30	0.0690	0.44	116

The second model reported in Table 3.2 is used for calculating the FRGC weight for a MEDPAR discharge. In this case, the weight for a MEDPAR discharge in FRG k is given by

$$W(k,x) = \exp(ax)*w_k, \qquad (2)$$

where x is defined as before. In this model, no effect of interrupted stay is used, as each discharge in the interrupted stay is paid separately. This same regression is used for the standard weights, the HSRV weights, and the fair weights.

Table 3.3 shows similar information for the regression of the log of cost per case (rather than charge). These regressions differ from those reported in Carter et al. (1997) in that they are based on the entire sample (rather than the half sample used in the earlier paper) and use the natural log rather than the log to the base 10. The results, however, are very similar in that the R-squares are almost identical and the coefficients are positive and usually significant.

In all RICs except that for stroke, we used any positive coefficients for these indicators, even if they were not significantly different from 0. It is likely that cases with comorbidities and interrupted stay do cost more and that it is just the small number of cases that makes it difficult to measure the effect with precision.[2] Stroke, on the other hand, has a large sample size and thus the measured value of almost 0 is measured quite precisely and could well be approximated by 0. A negative coefficient was measured only for the cost regression using UDSmr cases RIC 4 and for both charge per case regressions in RIC 1, and we did not use these negative coefficients.

A comparison of the cost and charge regressions show that they appear to be predicted equally well by the FRGs, comorbidity indicator,

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[2] If all Medicare cases in a single calendar year were available for analysis, the sample size would approximately triple. This should allow one to measure effects accurately enough that any factor that is not significant at the 0.05 level could be assumed to be 0.

Table 3.3

Cost Data: Coefficients for Interrupted Stay and Comorbidity from Regressions of Log of Cost per Case, Controlling for FRG and Coefficient for Comorbidity from Regression of Log of Cost per Discharge Controlling for FRG

	Cost per UDSmr Case						Cost per MEDPAR Discharge			
		Interrupted Stay		Comorbidity		Sample		Comorbidity		Sample
RIC	R-Square	coef.	t-stat	coef.	t-stat	Size	R-Square	coef.	t-stat	Size
1	0.22	0.3097	18.68	0.0024	0.36	28,775	0.19	0.0011	0.16	29,791
2	0.19	0.4956	6.46	0.0846	1.79	1,142	0.14	0.0467	0.99	1,200
3	0.19	0.3807	6.23	0.0966	3.25	1,946	0.16	0.1035	3.49	2,025
4	0.13	0.3842	2.92	0.0000	NA	629	0.10	0.0137	0.20	664
5	0.31	0.4128	7.39	0.2404	7.13	2,556	0.25	0.2158	6.41	2,672
6	0.14	0.5167	10.02	0.0984	3.96	4,075	0.11	0.0979	4.00	4,204
7	0.13	0.3775	14.10	0.1409	10.12	13,909	0.10	0.1164	8.41	14,293
8	0.18	0.3893	13.36	0.2171	14.90	17,280	0.15	0.2100	14.53	17,608
9	0.10	0.5517	10.59	0.1700	5.83	3,934	0.07	0.1575	5.49	4,038
10	0.14	0.4531	4.48	0.0436	0.86	1,223	0.11	0.0388	0.78	1,252
11	0.16	0.3967	3.64	0.2699	5.81	1,295	0.15	0.2593	5.57	1,324
12	0.13	0.5900	13.91	0.0616	2.60	3,556	0.08	0.0614	2.62	3,738
13	0.18	0.7517	4.86	0.1412	1.68	262	0.08	0.1354	1.62	284
14	0.26	0.4140	7.57	0.1599	5.96	2,269	0.22	0.1629	6.11	2,330
15	0.12	0.3436	4.61	0.0788	2.48	1,834	0.10	0.0731	2.31	1,887
16	0.07	0.5287	3.62	0.2154	3.09	1,181	0.05	0.1817	2.66	1,203
17	0.16	0.0810	0.50	0.2905	3.38	330	0.13	0.2581	2.94	341
18	0.17	0.4738	11.94	0.1195	6.85	4,986	0.14	0.1177	6.68	5,176
19	0.31	0.3106	1.96	0.0943	0.83	232	0.26	0.0065	0.06	246
20	0.36	0.1352	0.45	0.2030	1.32	117	0.30	0.0388	0.25	116

and interrupted stay (when used). For each RIC, the R-square and the t-statistics are similar for the regressions on charge and cost. There is no systematic variation in the value of the coefficient, with some coefficients larger and others smaller in the charge regression than in the cost regression.

Adjustment for Comorbidity and Interrupted Stay

The second step in the calculation of weights is to adjust the resource use for each case to eliminate the effect of comorbidities and, when UDSmr case is the unit of payment, the effect of interrupted stay. The adjusted resource use for a UDSmr case, with values x and y for comorbidity and interrupted stay, is, for charge-based weights,

$$A = \text{case\_charge}/\exp(ax + by).$$

Similarly, the adjusted resource use for a MEDPAR discharge with value x for comorbidity, is

$$A = \text{discharge\_charge}/\exp(ax)$$

and for cost-based weights:

$$A = \text{case\_cost}/\exp(ax).$$

These adjusted resource use values for each case (discharge) are then used to calculate the relative adjusted weight in each FRG k, w_k. In the next subsections, we describe the different algorithms that are used for the standard method, the HSRV method, and for fair weights.

Standard Method for FRG Relative Adjusted Weights

The algorithm for the calculation of standard relative weights is straightforward: Standardize the adjusted charges for each case using the facility's payment factor, eliminate statistical outliers (cases that differ from the FRG mean by more than three standard deviations in the log scale), average the adjusted charges in each FRG, and divide the average adjusted charge in each FRG by the grand average adjusted charge.

With standard weights, one needs to know the facility payment factors to calculate the weights and, as explained further in Section 4, one needs to know the CMI of the hospital (and therefore the weights) to calculate the payment factors. The circularity can be broken using an iterative procedure. We first calculated FRG weights from the HSRV method, and then used that case mix index to get corresponding payment factors. We used these payment factors to get a first version of standard weights, and then used this first version of standard weights to get new payment factors and then new standard weights. We found such a small change in the formula for the payment factor that we decided it was unnecessary to iterate further.

HSRV Method for FRG Relative Adjusted Weights

In the HSRV method, adjusted charges are standardized at the hospital level using hospital-specific charges--so charges for a patient at a hospital with high average charges are counted as less resource use than charges at a hospital with low average charges. The average weight or CMI is used to account for the variation in patients across hospitals.

In the HSRV method, the total adjusted charge for each case is divided by the average adjusted charge for the hospital in which the case occurred. The resulting ratio is then multiplied by the hospital's CMI to produce a hospital-specific, relative value. This relative value can be viewed as a charge that has been standardized by the hospital's own charging behavior, in contrast to the standard method where the charge is standardized by the payment factor.

The process of calculating the weights is iterative. Initial values are chosen for the CMI of each hospital (we used a CMI of 1 for each hospital). FRG adjusted weights are then set in proportion to the average value of the hospital-specific, relative value. These result in a new CMI for each hospital and therefore new hospital-specific, relative values. The process is continued until there is convergence between the weights produced at adjacent steps, for instance when the maximum difference is less than 0.0001. Earlier work showed that the algorithm is not sensitive to starting values of the CMI (Rogowski and Byrne 1990; Carter and Rogowski, 1992).

After the first iteration, we eliminated statistical outliers defined as cases that differ from the FRG mean by more than three standard deviations in the log scale of HSRV standardized charge.

Fair Weights

With fair weights the relative adjusted weight is calculated so that the average adjusted standardized payment, including outlier payments, will be proportional to the average adjusted standardized charge in the FRG. This contrasts with the previous two weight calculations in which only the standardized FRG payment is set proportional to the average adjusted standardized charge. Payment factors are used to account for the variation in hospital costs across facilities. Our algorithm is based on the assumption that the difference between fair weights and standard weights will have little effect on the identity of outlier cases, but will affect the amount each outlier case is paid.[3]

We simulated payment using the standard weights calculated previously and a fixed loss outlier policy that accounted for 5 percent of total payments and had a marginal cost factor of 0.8.[4] This identified each outlier case. Let $x = 1$ if the case is an outlier. Then the standardized payment for the case (i.e., the payment divided by the hospital's payment factor) will be

$$P = Rw_k + x(ccr^*C - 0.8^*(Rw_k + L)), \qquad (3)$$

where

R = the national payment rate,

w_k = the relative adjusted weight for the case,

C = the standardized charge for a case (i.e. the charge divided by the hospital's payment factor),

L = the fixed loss amount, and

ccr = the hospital's cost-to-charge ratio.

In fair weights, w_k is calculated so that the average value of P within an FRG is proportional to the average value of C. Setting the expectation of the right-hand side of equation (3) equal to the average value of C and solving for w_k yields

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[3] This assumption could be removed by iterating on the calculation of fair weights. One would repeat the procedure using the weights calculated in the preceding iteration. However, as we show in Section 6, the weights we calculated do have the property that payment is proportional to cost at the case level.

[4] The reader who is not familiar with how outlier amounts are calculated will find this information in Section 5.

$$w_k = (AVGC - 0.8*(OUTC - AVGX*L))/(R*(1 - 0.8*AVGX)),$$

where

OUTC = avg(x*ccr*C),
AVGC = avg(C)
AVGX = avg(x).

Relative Weights for FRG-Comorbidity-Interrupted Stay Groups

The next step in the algorithm is to calculate a relative weight for each relevant combination of FRG, comorbidity, and interrupted stay by putting back the effects of comorbidity and, for UDSmr cases only, of interrupted stays. Equation 1 (page 28) is used when the unit of payment is a UDSmr case, and equation 2 (page 30) is used when the unit of payment is a MEDPAR discharge. The final step of the algorithm is to multiply by the normalizing constant so that the average weight per case (or per discharge) is 1.

4. HOSPITAL-LEVEL ADJUSTMENTS

In this section, we determine the formula for the payment factors that adjust each hospital's payment to account for justifiable differences in cost that are beyond the hospital manager's control. The analyses reported here compare weights calculated using the different procedures presented in Section 3 and provide an evaluation of the ability of the FRGCs (or FRGCIs) to explain hospital-level costs. We also want to understand which factors--justifiable or not--affect cost. Even if policy makers would not want to pay for such factors in an RPPS, the analysis will help us understand the effect of current incentives and therefore the likely effects of an RPPS.

The tool used in these analyses is multivariate regression with the dependent variable giving the average cost per case at a particular hospital. The general specification is that

$$C = f(CMI, WI, X),$$

where

C = average cost per case at a hospital,

CMI = the case mix index (i.e. the average value of the weights for the hospital's cases) to control for the relative intensity of care required by the hospital's cases,

WI = wage index at the hospital as a proxy for input prices faced by the hospital, and

X = a vector of additional explanatory variables that affect a hospital's production function, such as its teaching program, proportion of low income patients, etc.

Following usual practice, we use the natural logarithm to transform cost and examine different specifications depending on the purpose of the analysis (Sheingold, 1990). For evaluating the ability of our case mix groups and weighting methodologies to explain hospital costs, we put the logarithm of CMI on the right-hand side. When developing the formula for the payment factor, because the payment for each case is proportional to the weight for the case, we subtract the log(CMI) from the log of cost and use this CMI-adjusted cost as the dependent variable.

In one set of evaluation regressions and in the payment regression, we restrict the elements of X to variables that stand for concepts clearly suitable for payment and currently used for payment in the acute care PPS: the size of the teaching program, the size of the low income population, and an indicator for location in a large urban area as well as the area wage index. In additional regressions we examined other possible correlates of cost that are probably not suitable for payment, such as type of rehabilitation facility and hospital size. We use an indicator for the time period during which the facility was certified as a measure of the extent to which the hospital was under pressure to control its costs from the TEFRA payment rules.

CASE MIX INDEX USED IN ANALYSES

The case mix index is the average of the FRGC (or FRGCI) weights. For both the standard weights and the UDSmr case weights, we use two different versions of the CMI because of the circularity inherent in the relationship between the CMI, the payment factor, and the weight assigned to transfer cases.[1] The CMIs differ in the way they assign case weight to transfer cases. The first CMI counted each transfer case at the full weight for its FRGC (or FRGCI) group. This first CMI was then used to get the formula for hospital payment adjustments.[2] The payment factors were then used to analyze the cost of transfer cases. Section 5 describes the formula for determining the fraction of the FRGC (or FRGCI) weight that should be assigned to each transfer case. The second CMI uses this method to assign weights to transfer cases. We show that the difference between these two methods of calculating the CMI has little measurable effect on the payment factor; thus we did not go back and recalculate the standard weights after the analysis of transfers was completed. For evaluating the weighting method, we used this second method of valuing transfer cases in calculating the CMI for each of the five weight methods because it is more accurate.

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[1] Transfer cases that stayed less than the arithmetic mean LOS for the FRG group were omitted from the calculation of weights, but all transfers are used in the calculation of the CMI and hospital cost per case.

[2] Getting the payment factor actually involved several steps. As explained in Section 3, we first calculated HSRV weights, averaged them to produce a CMI, and used these CMIs to get a first version of the payment factors. We then used these payment factors to create standard weights which we then used to create a new set of payment factors and a second set of standard weights. This second set of standard weights produced similar payment factors to the first set of standard weights (to within less than 1 percent).

All other variables used in the analysis were defined in Section 2.

EVALUATION OF WEIGHT METHODS

Table 4.1 shows how well the CMIs from each of the five methods of calculating FRGC (or FRGCI) weights predict hospital level costs when combined with all of the possible payment factors. Clearly the variation among hospitals in the resources needed by the average patient is a major source of the variation in cost among hospitals. The t-statistic on the coefficient of CMI exceeds 10, no matter which method is used to calculate the weights.

The coefficients on the possible payment factors are insensitive to the method used for weighting cases. In all cases the wage index is

Table 4.1

Regression of Log of Hospital Cost per Discharge (Case) on Possible Payment Factors and Case Mix Indices Calculated by Alternative Weights (Hospital Weighted)

	Standard Weight		UDSmr Case		Cost Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat
CMI	1.402	10.66	1.409	11.30	1.334	10.73
Log of wage index	0.377	3.13	0.365	3.03	0.360	2.99
Fraction Medicaid	0.644	3.60	0.633	3.53	0.657	3.69
Large urban area	0.013	0.37	0.014	0.39	0.019	0.54
Teaching	0.200	1.18	0.207	1.21	0.183	1.08
Intercept	9.368	---	9.390	---	9.366	---

	HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat
CMI	1.291	10.36	1.337	10.68
Log of wage index	0.374	3.08	0.377	3.13
Fraction Medicaid	0.682	3.80	0.643	3.56
Large urban area	0.015	0.43	0.014	0.40
Teaching	0.170	0.99	0.198	1.17
Intercept	9.364		9.328	

NOTE: Based on 341 hospitals. R-squares are 0.38, 0.40, 0.38, 0.37, and 0.38, respectively.

highly significant and its coefficient varies only from a low of 0.360 (with cost-based weights) to a high of 0.377 (with fair weights). The percentage of Medicare cases for which Medicaid is also a payer is also highly significant and of similar magnitude in all the regressions (range is 0.633 to 0.682).

The coefficients of large urban area and teaching are never significantly different from zero. Although these two variables are positively correlated, the correlation is not the cause of our inability to measure effects. Each remains insignificant when the other is removed from the regression. (Results are not shown in detail.[3]) Using a dummy variable to distinguish teaching hospitals instead of the ratio of residents to average daily census also does not produce a significant teaching effect. As discussed in Section 2, there may be errors in our measurement of the size of some teaching programs. Random errors in measurement would tend to bias the coefficient of teaching toward 0, which may be occurring here.

One problem with the regressions is that the coefficient on the CMI does not equal 1. The underlying assumption of a PPS is that payments should be in proportion to the case weight adjusted for payment variables. These regressions show that, unless payments are further modified by outlier adjustments and/or additional facility adjustments, payments are likely to be less than costs for hospitals with a high CMI and more than costs for hospitals with a low CMI. In all five regressions, the hypothesis that the coefficient is 1.0 with $p < 0.01$ can be rejected.

Comparisons among the five different weighting methods show no one single method as being preferable based on these regressions. The UDSmr case regression has a slightly higher R-square than the other regressions. The HSRV weight regression has the coefficient on the CMI which is closest to 1.0, although it has a slightly lower R-square. The good performance of the HSRV weights suggests that there may be hospitals that have systematically higher or lower costs and that these cost variations are not captured by the payment factor used to standardize costs in the standard weighting method.

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[3] In Appendix Table A.3, we show that, when the large urban area indicator is excluded from the payment regression, teaching is still not significant.

One would expect the performance of fair weights to be worse than other weights in these regressions because fair weights take into account variations among hospitals in outlier payments, and these payments are not included as explanations of cost. However, fair weights perform at least as well as standard weights here; consequently, we may hope that fair weights are more accurate than standard weights in our simulations that pay outlier payments. Using R-square and distance from 1 on the CMI coefficient as criteria, the performance of cost weights falls in between the other weights. As explained earlier, these weights introduce difficulties in timely updating of payment parameters.

As may be seen by comparing Table 4.1 to Table A.1 in the Appendix, the results are unchanged when we weight each hospital by the number of sample cases at the hospital. Although one might expect that the case weighted regression is more efficient, the coefficients are very similar to the hospital weighted results in Table 4.1.

The finding of coefficients greater than 1 on all CMIs is consistent with weights that are compressed--i.e., with weights that undervalue expensive FRGCs and that overvalue inexpensive FRGCs. The same finding is, however, also consistent with other possible problems in the model. One alternative is that there are omitted variables that affect costs and that are correlated with the CMI. We explore these possibilities in the next two subsections. The final subsection discusses the payment factor formula which we use in the remainder of this report.

CODING

We believe that coding errors leading to problems with weight calculations constitute one of the problems with these data, although this may not be the only problem. Poor coding is one of the possible causes of weight compression.[4] If coding errors are random, then each FRGC (or FRGCI) will contain a mixture of average cases along with cases specific to the group. Thus, the weight for the group will be moved toward the average (Pettengill and Vertrees, 1982). It seems clear that weights in the acute care PPS were compressed in the early PPS years (Thorpe, Cretin, and Keeler, 1988; Lave, 1985) and that coding was one of the reasons for this compression (Carter and Rogowski, 1992). Many of the changes in coding in response to the PPS were improved coding rather than coding for gaming purposes (Carter, Newhouse, and Relles, 1991).

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[4] Lave (1985) has a particularly clear discussion of the possible causes of compression.

As the advisory panel for the first part of this study suggested, the rules for scoring each FIM item would benefit from further specificity. The developers of the UDSmr are in the process of developing more specific guidelines for scoring the FIM instrument, but the data we have do not reflect this work. Our study is based on data that have never been used for large scale, inter-hospital analyses. The UDSmr gives national statistics to participating hospitals. Possibly, they may have tried to norm their scores so that their average case looked like the national average. This would help explain why the FIM-FRGs do splendidly at explaining inter-patient variation in resource use, but do only slightly better at explaining inter-hospital variation in resource use than inter-patient resource use. (One would expect that average resource use at the hospital would have a smaller component of random noise because of the law of large numbers.)

The use of FRGs rather than raw FIM scores to characterize patients should mitigate the effect of miscoding of FIM items. Since the FRGs are based on ranges of FIM motor and FIM cognitive scores, and since we limited the number of FRGs in each RIC to at most five, the only coding errors that affect FRG assignment are either large errors or scores near the FRG cutpoints.

In addition to possible coding errors in the FIM, there is the possibility of miscoding of rehabilitation impairment categories (RICs). The Clinical and Functional Status technical advisory panel believed that, with the current set of RICs, some cases provide opportunities for alternative assignment, such as a patient with neck pain due to osteoarthritis who could be classified in an arthritis category (Carter et al., 1997). In an operating payment system, it would be possible to define these rules reasonably carefully and monitor assignment. However, we do not know whether similar cases are in fact classified into different RICs in our current data base. If they are, and if the different RICs lead to different weight assignment, it would increase weight compression.

The only variable for which we have specific evidence that coding errors exist is the comorbidity indicator. The comorbidity indicator is 1 if the patient has one of a specific set of comorbidities and 0 otherwise.[5] Rehabilitation facilities are asked by Medicare to code comorbidities and complications, but this information was never used for any purpose. Thus it is likely subject to errors, particularly errors of omission.

In the early years of the acute care PPS, the proportion of cases with coded comorbidities increased dramatically, probably in large part because of earlier undercoding. In the beginning of FY 1988, the DRG system was changed so that, for the first time, patients who were 70 or older were put into a different DRG if they had a comorbidity than if they did not have a comorbidity. The result was a dramatic increase in the proportion of patients over 69 with comorbidities. A research study used "gold standard' coders to recode a random sample of hospital medical records from both FY 1987 and FY 1988. They found that the comorbidities coded in FY 1988 were usually correct, but that many of the medical records for 1987 cases coded by the hospitals without comorbidities contained evidence that the patient had a comorbidity--since the comorbidity did not affect payment it was not coded. Similarly, we suspect that the Medicare records for our sample of rehabilitation cases omit many existing comorbidities.

There is evidence to support this suspicion. If exempt unit discharge records are coded by the same medical record technicians that code the hospital's PPS records, then we would expect that errors might be less frequent in exempt units than in freestanding facilities and LTC facilities. As shown in Table 4.2, exempt units do code a higher fraction of their cases as having comorbidities.

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[5] See Carter et al. (1997) for further information about the comorbidity variable.

Table 4.2

Fraction of Cases with Coded Comorbidities, by Type of Facility

	Percent Comorbidity
Freestanding	16.5
Exempt unit	25.5
Long term care	14.9

Is the higher rate of coding of comorbidities a reflection of more coding or of sicker patients? If it is due to coding, then one would expect that the difference in resource use between cases with comorbidity and cases without comorbidity would be greater for cases in exempt units than for cases in other facilities. Such is in fact the case. We reran the regressions for the MEDPAR discharge reported in Table 3.2, adding two additional variables: a dummy variable that distinguished freestanding and LTC hospitals from exempt unit and the interaction of freestanding with comorbidity. The interaction was negative in 15 of the 19 RICs.[6] In all five of the cases where the interaction was significantly different from 0 ($p < 0.05$), it was negative (RICs 6,7,10,16, and 18). Consequently, we believe that coding is one of the reasons for the apparent problems in the FRGC weights.

Errors in coding comorbidities will lead to compression in the FRGC weights because the lower-weighted FRGCs without comorbidity will be too high relative to the higher-weighted FRGCs with comorbidity. However, the distortion of the CMI caused by coding need not be as simple as compression. Because we believe that undercoding of comorbidity varies across hospitals, the relationship between the CMI and costs depends on the CMI of hospitals that are undercoding--which need not be those with the lowest or highest CMI.

OMITTED VARIABLES

We explored several variables that might explain hospital costs and thus, if included in the regression, might lead to an improved fit of the payment variables to cost. Although some variables do explain hospital costs, none removes the apparent compression in the CMI.

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[6] RIC 1 (stroke) was omitted from the analysis just as in Table 3.2.

One variable that was not significant was hospital size. One might expect that there would be economies of scale and so, after controlling for the CMI, larger hospitals would be less expensive.[7] We used a number of Medicare rehabilitation cases on the calendar year 1994 MEDPAR to measure size.[8] We examined the log transformation as well as groupings according to size, but none was significant. We experimented with the interaction of rehabilitation size with type of facility, reasoning that freestanding facilities would show clearer economies of scale than exempt units, which can pool some services (administration, cleaning, etc.) with their parent inpatient hospital. Although the coefficient for log of cases in a freestanding facility was negative it never reached a 0.05 significance level.

Two variables that clearly affect hospital cost are type of facility and time period of certification. As shown in Table 4.3, freestanding hospitals are noticeably more expensive than exempt units after controlling for CMI, and the significant payment factors (wage index and fraction Medicaid).[9] Furthermore, facilities certified in recent years are also more expensive than facilities in existence since the beginning of PPS. This likely reflects the differential pressure that TEFRA exerts to control costs. Because TEFRA payments were similar to PPS payments during the early PPS years, payment increases were substantially lower than inflation as measured by the HCFA hospital market basket. Thus these older facilities had to reduce their costs. Because newer hospitals can establish their own baseline costs they are under much less pressure than older hospitals to control costs. Some of the newest hospitals in the group were still establishing their baseline costs in 1994 and even had an incentive to increase costs.

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[7] There is an argument for the opposite effect. Indeed, in the acute PPS, larger hospitals are more expensive, probably because of the higher intensity of care than similar patients receive in a smaller hospital.

[8] We could not use the number of sample cases because some hospitals contributed cases to UDSmr only during part of the year, and several of the LTC hospitals contributed only part of their cases.

[9] Poor coding of comorbidities by freestanding facilities could account for only a small fraction of the difference in costs shown.

Table 4.3

Regression of Log of Hospital Cost per Discharge (Case) on Payment Variables, Provider Type, and Period of Certification

	Standard Weight		UDSmr Case		Cost Weight		HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
CMI	1.531	12.23	1.524	12.84	1.471	12.43	1.439	12.14	1.460	12.25
Log of wage index	0.477	4.87	0.469	4.79	0.470	4.83	0.475	4.85	0.478	4.89
Fraction Medicaid	0.376	2.2	0.367	2.15	0.383	2.26	0.399	2.33	0.375	2.20
Compared to exempt unit										
Freestanding	0.166	5.12	0.166	5.15	0.167	5.20	0.173	5.32	0.165	5.12
LTC	0.086	1.13	0.089	1.17	0.091	1.19	0.091	1.19	0.090	1.18
Compared to before FY85										
FY85 to FY89	0.057	1.69	0.062	1.85	0.065	1.95	0.058	1.73	0.057	1.72
FY90 or later	0.153	4.31	0.156	4.40	0.159	4.50	0.157	4.41	0.153	4.32
Intercept	9.296	---	9.316	---	9.291	---	9.289	---	9.253	---

NOTE: Based on 341 hospitals. R-squares are 0.46, 0.48, 0.47, 0.46, and 0.47, respectively.

These omitted variables do not move the coefficient on the CMI closer to 1. Rather the CMI coefficient increases. It is not clear why this occurs.

FACILITY ADJUSTMENT PAYMENT FORMULA

We took the approach used to develop total payment facility adjustments during development of the capital PPS for acute hospitals (DHHS, 1991). In this method, the CMI-adjusted cost per case at each hospital is regressed on the payment variables and the resulting coefficients are used to develop the hospital-specific payment factor. This method is also similar to the method used for teaching and disproportionate share payment factors in the acute care PPS for operating payments. The effect of local wages is handled differently in the acute PPS; there the cost reports were used to estimate the fraction of operating payments that were due to wages and a factor was based on this fraction.

Table 4.4 shows the derivation of the facility payment adjustment used in this study. The results of the first step in the iteration (a regression of the log of cost per case minus the log of the HSRV CMI on the local area hospital wage index and the fraction of Medicaid) are shown in columns 1 and 2. The dependent variables are the only two payment variables found in our analysis to be significant These payment factors were then used to standardize the charges for each MEDPAR discharge to estimate standard method weights. The second regression in the table is a regression of the log of cost minus the log of the CMI produced in this first iteration on the same variables. This produced a slightly different estimate of the affect of payment factors. This estimate was then used to recalculate the standard method weights with the result shown in the third step, which we viewed as close enough to stop the process. A similar process was used for UDSmr cases with the result shown in the last regression. (A second iteration was indistinguishable from the first.)

The payment adjustment that we used throughout the remainder of this report for MEDPAR discharges at hospital i is

Table 4.4

Iteration of Facility Payment Adjustment. Regressions of the Log of CMI-Adjusted Cost per Case

	Step 1:		Step 2: MEDPAR discharge		Step 3: MEDPAR discharge		Step 3: UDSmr Case	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
Log (wages)	0.435	4.07	0.448	4.20	0.448	4.21	0.437	4.20
Fraction Medicaid	0.800	4.41	0.801	4.44	0.803	4.45	0.820	4.80
Intercept	9.297	---	9.295		9.295	---	9.399	---

NOTES: R-square is 0.09 on all four regressions. The CMIs used here gave transfer cases full FRGC (or FRGCI) weight.

$$A_i = \exp(0.448*\log(\text{wageindex}) + 0.803*\text{Medicaid}).$$

For UDSmr cases the payment factor is

$$A_i = \exp(0.437*\log(\text{wageindex}) + 0.820*\text{Medicaid}).$$

The analysis of transfer cases discussed in Section 5 presents a more appropriate way to pay for transfer cases than to pay such a case based on its full FRGC (or FRGCI) weight. To determine whether this accounting of transfer cases would have a substantial effect on the payment factor, we reran the regression for the standard method CMI after revising the weights for transfer cases. As shown in the first regression in Table 4.5, the coefficient on the wage index increases from 0.448 to 0.451 or 0.7 percent. The coefficient on the fraction Medicaid increases by 0.9 percent. In view of the less than 1 percent change in each coefficient, we did not recalculate the standard method weights or change our planned adjustment factor.

The other regressions in Table 4.5 show that the payment factor coefficients are stable despite changes in the method used to calculate the CMI in the dependent variable. The R-square is slightly higher (0.11 versus 0.09) because of the more accurate accounting for transfer cases.

Table 4.5

Comparison of Facility Payment Regressions by CMIs Calculated from Alternative Weights (Hospital Weighted)

	Standard Weight		UDSmr Case		Cost Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat
Log (wage index)	0.451	4.35	0.446	4.29	0.440	4.27
Fraction Medicaid	0.810	3.60	0.812	4.75	0.799	4.71
Intercept	9.377	---	9.401	---	9.377	---

	HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat
Log (wage index)	0.441	4.26	0.477	4.33
Fraction Medicaid	0.803	4.71	0.788	4.64
Intercept	9.375	---	9.348	

NOTE: R-square is 0.11 on each regression. In calculating the CMIs, transfer cases are assigned a per diem weight up to the maximum weight for their FRGC (or FRGCI).

The payment coefficients are also insensitive to whether the payment regression is hospital-weighted or case-weighted, as may be seen by comparing Table 4.5 with Table A.2. Because the practice of using hospital-weighted regressions for the payment factor has been used in the acute care PPS and because the empirical results are so similar, we used it here. Either case-weighted or hospital-weighted regressions provide unbiased estimates of the coefficients, but case-weighted regressions should be more efficient. Case-weighted regressions account for the fact that there is more random variation in data from small hospitals than large ones and produce minimum variance unbiased estimates of the coefficients. Although it has little effect on our estimates, case-weighted regressions are theoretically better.[10]

For completeness, Table A.3 shows what would happen if teaching were left in the payment formula. It is never even marginally significant and never numerically large.

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[10] Empirical comparisons of case weighted and hospital weighted regressions of cost per acute case are reported in Sheingold (1990) and Carter and Rogowski (1993). In these papers, there were noticeable differences in the magnitude of some coefficients--of the order of 27 to 28 percent.

5. CASE-LEVEL PAYMENT ADJUSTMENTS

TRANSFERS

Some cases are transferred to another hospital before the patient has received the full course of rehabilitation therapy. Most of these transfers are to acute care facilities and occur because the patient has encountered a medical condition or event requiring acute care management. A small number of transfers are from one rehabilitation facility to another and, according to our expert panel, they are often at the patient's request. In any case, since the patient has not received the full course of treatment, it may be appropriate to not provide the full FRG payment. A reduced payment that reflects the actual cost of the case will eliminate any financial incentive for unnecessary patient shifting.

In this section, we analyze the costs of these transfer cases and then recommend a per diem payment policy that will result in short-stay transfer cases receiving payment that approximates the treatment cost. Under this policy, longer-stay transfer cases receive the full FRG payment, and payment increases smoothly with LOS until it reaches the full FRG payment. We first examine whether per diem costs vary across FRGCs or whether they are the same for all groups. We show that, after controlling for LOS, the cost of transfer cases in different FRGCs is roughly proportional to the FRGC weight divided by the arithmetic mean LOS. The second analysis develops a simple payment model which captures the major variation across both LOS and FRGC group. This model is easy to administer and will likely be robust to changes in the data.

The structure of our analysis is similar to that used to examine the costs of transfer cases in the acute care PPS (Carter and Rumpel, 1993a). That analysis demonstrated the value of a new transfer policy that HCFA chose to implement for FY 1996 and subsequent years. The policy we recommend here for the RPPS has a structure similar to the acute care PPS policy. Consequently, we review the acute care PPS policy and supporting analyses in the first subsection below. Then we present a brief description of transfers from rehabilitation facilities.

The final subsections describe our analyses and a recommendation for paying these cases.

Payment for Transfers Under the Acute Care PPS

Cases transferred from one acute facility to another acute facility are paid a graduated per diem rate at the sending facility. The payment amount for a case in DRG k transferred from hospital i is given by

$$R*A(i)*d(k)*(m + 1),$$

where

R = the national payment rate,

A(i) = the facility payment adjustment factor for hospital i which takes into account teaching, disproportion share, geographic location, and area wages,

d(k) = the daily weight for DRG k calculated as the DRG weight divided by the geometric mean LOS, and

m = LOS for the transfer case.

The payment amount is capped at the DRG payment, so all transfer cases that stay more than the geometric mean LOS for the DRG minus one day receive a full DRG payment rather than a per diem amount.

This payment formula was chosen after analyzing the costs of short stay transfer cases. Carter and Rumpel (1993a) found that each additional day for a transfer case added, on average, about $R*A(i)*d(j)$ to the cost of the case and that a fixed cost about equal to the cost of one additional day was associated with a case.[1] The costs for a transfer case are well approximated by a simple model:

$$cost = a + b*m,$$

where the coefficient $b = R*A(i)*d(k)$, and $a = b$. The payment formula thus pays each case an estimate of its costs.

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[1] Actually the formula is more accurate for medical transfer cases than for surgical cases. For surgical cases, the fixed cost of the case is higher than the per diem and the additional cost of an extra day is somewhat lower than the per diem.

Descriptive Statistics

Because many more stays are transfers when the discharge is the unit of analysis as when the case is the unit of analysis, we carried out our analysis in full using both units of payment. Transfers of UDSmr cases were defined based on the discharge setting recorded in the UDSmr. Any case with a discharge setting of 6 (acute unit of own facility), 7 (acute unit of another facility), or 9 (rehabilitation facility) is counted as a transfer. In addition, when the unit of analysis is the MEDPAR discharge rather than the UDSmr case, the discharges associated with the first part(s) of each interrupted stay were counted as transfers.

We developed a transfer case payment model that pays a per diem and is capped at the full FRGC (or FRGCI) payment for the case. We define a short stay transfer as a UDSmr case that ended in a transfer and also had an LOS less than the arithmetic mean LOS for its FRGCI. Similarly, we defined a short-stay transfer as a MEDPAR discharge that ended in a transfer and also had an LOS less than the arithmetic mean LOS for its FRGC. We used such cases as the basis of our analysis because we believed that they were the only ones likely to be paid the per diem and, therefore, their costs were most relevant to such a policy.

Table 5.1 shows that 5.59 percent of all UDSmr cases ended in a transfer and that 4.18 percent of UDSmr cases were short-stay transfers. MEDPAR discharges have about a 50 percent higher transfer rate than UDSmr cases. As also shown in Table 5.1, the transfer rate is higher at freestanding rehabilitation facilities and LTC hospitals than at exempt units. This probably reflects the ability of a unit that is part of an acute care hospital to keep an ill patient in a rehabilitation bed because, should acute care be required, it would be immediately available. If this is the correct interpretation, it reflects the valuing of patient care standards over financial incentives, since the same acute care hospital would receive the PPS payment.

Almost all transfers are transfers to acute care rather than transfers to rehabilitation facilities. Only 5.52 percent of UDSmr case

Table 5.1

Percentage of UDSmr Cases and MEDPAR Discharges That Are Transferred and Percentage Transferred with LOS Less than Group Mean, by Provider Type

	UDSmr Cases			MEDPAR Discharges		
	N	% Transfer	% Short-Stay Transfer	N	% Transfer	% Short-Stay Transfer
Freestanding	44,908	6.14	4.47	46,649	9.29	7.06
Exempt unit	47,520	4.95	3.87	49,018	7.60	6.22
Long-term care	3,316	7.18	4.58	3,435	10.16	6.73
Total	95,744	5.59	4.18	99,102	8.48	6.63

transfers (and 3.64 percent of MEDPAR discharge transfers) are transfers to rehabilitation facilities. For UDSmr cases, 78 percent of transfers from exempt rehabilitation units are to the acute care section of the same facility.[2]

Table 5.2 shows transfer rates within each RIC. The lowest rate of transfer is for RIC 8, lower extremity joint replacement. This makes sense in that most of those who undergo this major surgery are otherwise healthy. The highest transfer rates are found in RIC 15 (pulmonary) and in the very small RIC 13 (amputation, other than lower extremity).

Because many FRGCs have long average LOS, there are many transfer cases that have both a long LOS and a LOS less than the average for their FRGC group. Figure 5.1 shows the frequency distribution of each LOS for short-stay transfers for UDSmr cases and Figure 5.2 shows similar information for MEDPAR discharges. Many of the transfers that are the first parts of an interrupted stay have very short LOS.

Exploratory Analysis

In this section, we examine how the costs of transfer cases vary with LOS and FRGC (or FRGCI) weight. The primary purpose of the

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[2] For freestanding rehabilitation units, 139 cases (5.0 percent of UDSmr transfer cases for these facilities) were classified as being sent to their "own" acute care unit. It is not clear if this reflects coding error or if it reflects corporate relationships that are not shown in how Medicare classified the providers.

Table 5.2

Percentage of UDSmr Cases and MEDPAR Discharges That Are Transferred and Percentage Transferred with LOS Less than the Group Mean, by RIC

	UDSmr Cases			MEDPAR Discharges		
RIC	N	% Transfer	% Short-Stay Transfer	N	% Transfer	% Short-Stay Transfer
1	30,000	6.1	4.6	31,422	9.4	7.6
2	1,219	7.6	6.0	1,286	11.9	9.3
3	2,073	8.4	6.4	2,182	12.8	10.1
4	685	7.7	6.3	729	12.5	10.0
5	2,729	6.5	5.1	2,864	10.5	8.3
6	4,331	6.2	4.4	4,470	8.8	6.4
7	14,340	4.4	3.3	14,748	6.7	5.4
8	17,468	2.2	1.4	17,795	3.8	2.8
9	4,093	5.0	3.6	4,213	7.5	5.3
10	1,289	4.8	3.4	1,322	7.0	5.4
11	1,349	4.8	3.4	1,382	6.7	5.0
12	3,813	8.6	6.6	4,029	13.0	10.1
13	279	9.7	7.5	300	15.7	12.0
14	2,452	8.8	6.8	2,564	12.3	10.0
15	2,066	11.9	9.1	2,140	14.7	11.4
16	1,238	4.0	2.8	1,247	5.4	3.7
17	347	6.9	5.5	365	10.4	8.2
18	5,418	9.2	7.1	5,653	12.6	9.8
19	248	6.5	4.4	269	13.0	10.0
20	117	4.3	2.6	122	7.4	4.1
Total	95,744	5.6	4.2	99,102	8.5	6.6

analysis is to determine whether per diem costs for transfer patients vary with FRGC (or FRGCI) weight. The FRGs that we use were defined using LOS rather than costs. Although we have found that these FRGs predict costs (and charges), this could be exclusively (or predominantly) because they predict LOS and LOS predicts cost--i.e., the per diem costs are similar in each FRG group, but case costs vary among groups because LOS varies. On the other hand, it is plausible that comorbidities affect per diem costs because of the need for ancillary services and medications. In Carter et al. (1997), we show that the presence of a comorbidity causes a greater percentage

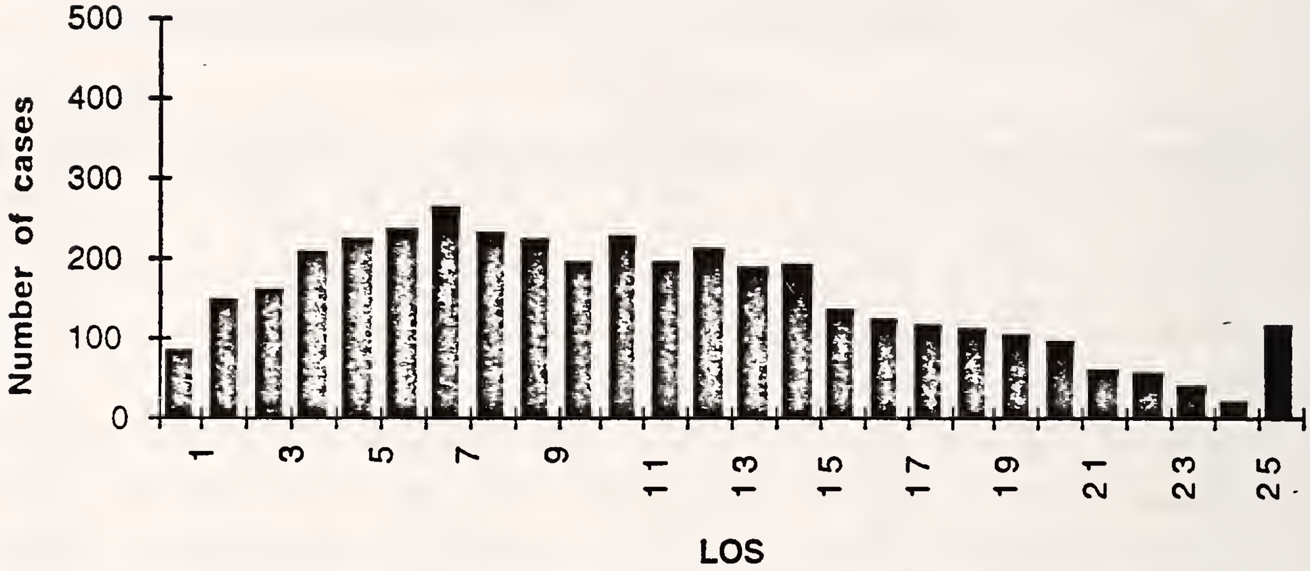

Figure 5.1--Distribution of Short-Stay Transfers by LOS (UDSmr^{SM} cases)

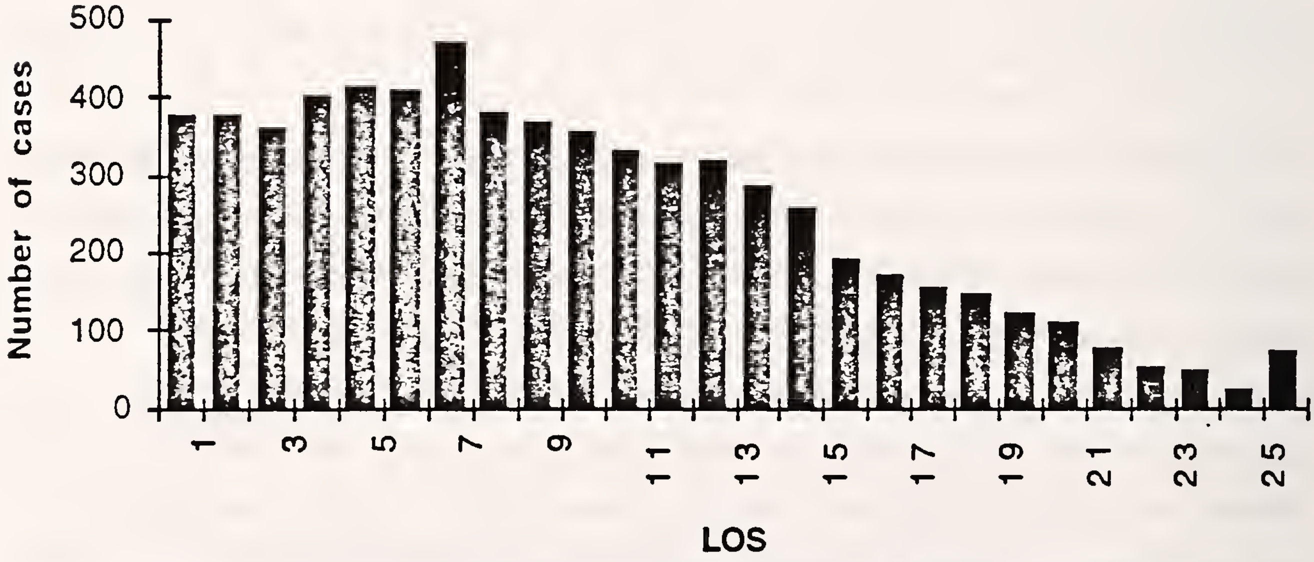

Figure 5.2--Distribution of Short-Stay Transfers by LOS
(MEDPAR discharges)

increase in costs than in LOS,[3] so it is also plausible that per diem costs vary with our FRGC groups--even if they do not vary with FRGs.

We began by calculating per diem weights for each FRGC group as the standard weight for a case in the FRGC divided by the arithmetic mean LOS for the FRGC. Since the case weights should be proportional to the cost of the resources used by a typical case in the group, this daily weight should be proportional to the cost of the resources used during a typical day in the FRGC.

Table 5.3 shows the distribution of FRGCs, discharges, and short-stay transfer cases by the percentage difference between their daily weight and the daily weight associated with the average case. For example, there are only two FRGCs with an average daily weight less than 80 percent of the overall average. These two FRGCs contain 684 discharges (0.7 percent of all discharges) and 14 short-stay transfer cases (0.2 percent of all short-stay transfers). The distribution is relatively tight, with 66.2 percent of FRGCs having daily weights within plus or minus 10 percent of the overall average. The daily weight of transfer cases is somewhat higher than for typical cases: only 31 percent of cases are less than the average for typical cases and almost 17 percent are more than 10 percent higher than average.

We next examine whether the per diem cost of transfer cases is proportional to these daily weights, after controlling for LOS. For each short-stay transfer case, we regressed the log of the standardized cost of the case on dummy variables denoting the LOS and on the log of the daily weight. The results are the first regression presented in Table 5.4. The daily weight and the LOS describe the standardized cost of transfer cases quite well with an R-square of 0.85. The costs of the

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[3] The coefficient on comorbidity in a regression of log of cost was statistically significant ($p < 0.01$) in 12 RICs vs. only 7 RICs for regressions on log of LOS. Further, in the RICs where comorbidity was significant in both regressions, comorbidity typically caused a 50 to 90 percent larger increase in costs than the increase in LOS. After controlling for FRG and interrupted stay status, the percentages by which comorbidity increased costs in these 7 RICs were: 23, 16, 21, 19, 24, 56, and 15. Similar percentages for the effect of comorbidity on LOS were: 13, 6, 16, 10, 15, 36, and 10. See Table 5.5 of Carter et al. (1997) for further details.

Table 5.3

Distribution of Daily Weight of MEDPAR Discharges Compared to Daily Weight of Average Discharge

Compared to Average, Daily Weight is (%)	FRGC Groups		Discharge		Short-Stay Transfers	
	N	%	N	%	N	%
≤ 80	2	1.2	684	0.7	14	0.2
80-90	11	6.7	3,851	3.9	97	1.5
90-100	46	28.2	49,982	50.4	1934	29.4
100-110	62	38.0	36,576	36.9	3,434	52.2
110-120	23	14.1	6,351	6.4	819	12.5
120-130	13	8.0	1,106	1.1	162	2.5
130-140	2	1.2	53	0.1	9	0.1
140-150	2	1.2	261	0.3	61	0.9
> 150	2	1.2	238	0.2	43	0.7
Total	163	100%	99,102	100%	6,573	100.0

transfer case do vary with the daily weight with a highly significant t-statistic ($p < 0.001$).

Although the coefficient is unlikely to be exactly 1.0 ($t = 4.06$, $p < 0.001$), it is much closer to 1 than to 0. The length of stay dummies compare the cost of the average transfer case with each LOS to the cost of a transfer case that stayed only one day. So, e.g., a two-day LOS costs 1.766 (= exp(0.569)) times more than a one-day stay in the same FRGC group. A three-day stay costs 2.53 times the cost of the stay and a four-day stay costs 3.32 times the cost of the stay. These data are consistent with there being both a per discharge cost and a per diem cost--a fact that we will use in developing a payment model in the next section.

The remaining entries in Table 5.4 are sensitivity analyses in which we vary the case weight calculation and the daily weight calculation. Because the UDSmr cases payment unit identified many fewer cases as transfers, we expected that these weights would be the most different from the weights for the MEDPAR discharge and chose to use this method as our second case weight calculation. As shown in the second column in the table, the daily weight remains highly significant

Table 5.4

Regressions of Log of Standardized Cost on Daily Weight and LOS, for Different Definitions of Daily Weight

	MEDPAR Discharge		UDSmr Case		MEDPAR Discharge		UDSmr Case	
	a.m. LOS		a.m. LOS		g.m. LOS		g.m. LOS	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
Daily Weight	0.808	17.09	0.774	13.85	0.563	16.51	0.609	13.46
LOS 2	0.569	24.71	0.600	13.91	0.571	24.51	0.604	13.88
LOS 3	0.929	39.81	0.915	21.54	0.932	39.42	0.920	21.50
LOS 4	1.199	52.87	1.242	30.41	1.202	52.36	1.248	30.31
LOS 5	1.349	59.83	1.417	35.10	1.354	59.27	1.426	35.04
LOS 6	1.558	68.96	1.573	39.23	1.562	68.24	1.581	39.10
LOS 7	1.725	78.78	1.759	44.47	1.730	77.95	1.768	44.32
LOS 8	1.854	80.68	1.865	46.35	1.859	79.81	1.875	46.20
LOS 9	1.960	84.49	1.986	49.12	1.963	83.33	1.995	48.94
LOS 10	2.036	87.16	2.043	49.54	2.041	35.87	2.054	49.24
LOS 11	2.117	88.88	2.155	53.48	2.121	87.42	2.166	53.23
LOS 12	2.226	92.25	2.253	54.67	2.235	90.64	2.269	54.34
LOS 13	2.282	94.67	2.292	56.30	2.286	90.74	2.300	55.47
LOS 14	2.362	95.27	2.399	57.88	2.362	90.11	2.395	55.95
LOS 15	2.419	94.62	2.465	59.76	2.422	90.54	2.471	58.53
LOS 16	2.483	88.60	2.522	57.70	2.500	82.96	2.544	56.58
LOS 17	2.521	86.16	2.551	57.15	2.517	75.01	2.549	53.73
LOS 18	2.606	86.05	2.635	58.11	2.592	69.64	2.636	52.68
LOS 19	2.643	85.81	2.706	59.36	2.684	64.45	2.742	52.85
LOS 20	2.716	82.76	2.752	59.26	2.710	62.22	2.780	51.73
LOS 21	2.801	81.20	2.826	59.75	2.813	64.16	2.860	51.61
LOS 22	2.856	72.66	2.861	53.65	2.890	48.33	2.861	45.33
LOS 23	2.867	61.35	2.920	53.39	2.930	29.94	2.848	39.65
LOS 24	2.862	57.97	2.908	47.70	2.575	8.04	2.990	36.75
LOS 25	2.946	42.51	2.961	39.58			3.026	29.44
LOS 26	3.057	43.11	3.103	35.75			3.036	9.41
LOS 27	2.987	42.16	3.078	44.39			3.166	26.69
LOS 28	2.949	38.70	3.047	45.66			3.198	25.30
LOS 29	3.050	13.62	3.237	22.08			3.518	10.89
LOS 30	2.954	16.14	3.047	29.87			3.129	21.19
LOS 31	3.017	13.48	3.090	18.96			3.293	10.20
LOS 32	2.908	9.19	3.295	17.60			2.977	9.22
LOS 33	3.565	15.93	3.371	25.06			3.303	10.23
LOS 35			3.257	17.40				
LOS 36			3.375	18.03			3.382	17.93
LOS 40	3.691	11.68	3.729	19.89			3.113	9.63
Intercept	9.143	66.17	9.036	54.03	8.334	88.27	8.449	65.25

NOTE: R-square for the regressions are, respectively, 0.850, 0.821, 0.835, and 0.807. Sample sizes for the regressions are 6573, 4000, 5898, and 3549.

and the coefficients are very similar. However, the fit is slightly worse than for the MEDPAR discharge weights.

The geometric mean LOS (g.m. LOS) is used in the acute care PPS rather than the arithmetic mean LOS (a.m. LOS) and, all other things equal, we would like to use procedures similar to the acute care PPS. Consequently, we also analyzed a daily weight calculated by dividing the standard weights for a discharge by the g.m. LOS for the FRGC and used a similar procedure for the UDSmr case. The last two regressions in Table 5.4 show that the fit is somewhat worse in these cases and that, although the cost of the transfer case varies with this daily weight, the constant of proportionality is further from 1 than when the a.m. LOS is used.

Some values of LOS do not appear in some of the four regressions in Table 5.4. This is because the sample of short-stay transfer cases varies across the regressions. In each case, we included only transfer cases that were shorter than the mean LOS for its group. For the MEDPAR discharges, the group is defined by FRG and comorbidity, while for the UDSmr cases, the group is defined by FRG, comorbidity, and interrupted stay. Since interrupted stays typically have longer LOS than other groups, there are a few transfer cases with LOS 35 and 36 that are counted as short-stay cases when compared to their FRGCI group, but not as short-stay cases when compared to their FRGC group. The g.m. LOS is shorter than the a.m. LOS and thus fewer cases are counted as short-stay transfers.

A Payment Model

The preceding analysis showed that, after controlling for LOS, the cost of a short-stay transfer case is roughly proportional to the daily weight and that, on average, one-day transfer cases cost more than each subsequent day of a longer transfer. These findings are consistent with the results of earlier analyses of transfer cases in the acute care PPS and suggest the following simple model for the standardized cost of a short-stay transfer case, C:

$$C = a*R*d(k)+b*R*d(k)*(m - 1) + \varepsilon,$$

where

a and b = regression coefficients,

ε = an error term,

R = the payment rate for a hospital with a payment factor of 1,

d(k) = the daily weight for FRG k calculated as the FRG weight divided by the mean LOS, and

m = LOS for the transfer case.

We estimated the payment rate assuming that total payment for the cases in this sample would approximate cost. The rates we used were R = $12,200 for the MEDPAR discharge case and $12,550 for the UDSmr payment case. Because this analysis needed to be performed before we knew how we would be paying transfer cases, these rates are slightly higher than the final rates used in the simulation (1.0 percent higher for the MEDPAR discharge run and 2.7 percent for the UDSmr case). The effect of these overestimates of R is to decrease the size of the coefficients a and b by the same percent.

Table 5.5 shows the results for the four regressions. The results of the MEDPAR discharge payment are quite similar to those for the UDSmr case payment. Using the a.m. LOS regression, a one-day transfer stay costs about one and one-half as much as a typical day in the FRGC (or FRGCI) and each additional day adds about the same amount as the typical day. Both numbers are measured with substantial precision. If the g.m. LOS is used, the one-day stay still costs about 50 percent more than each additional day. However, because the daily weight is larger than for the a.m. LOS, the coefficients a and b are reduced by between 12 and 17 percent.

Recommendation

We recommend paying each transfer case a per diem amount equal to the payment for the case divided by the a.m. LOS plus an extra amount equal to 50 percent of the per diem. This method should be relatively robust to changes in the case weight.

Table 5.5

Transfer Payment Regression

	UDSmr Case		MEDPAR Discharge	
	coef.	t-stat	coef.	t-stat
a.m. LOS				
Day 1	1.443	10.6	1.566	19.3
Subsequent days	1.038	94.7	1.018	134.9
g.m. LOS				
Day 1	1.280	11.6	1.340	20.9
Subsequent days	0.880	86.9	0.846	121.5

We choose the a.m. LOS rather than the g.m. LOS because the latter appears to give payments that match costs somewhat more accurately. (If the g.m. LOS is used instead, we would recommend that both the per diem and the extra payment be reduced to reflect the higher calculated per diem for nontransfer cases. A decrease of about 15 percent would be appropriate.)

OUTLIERS

Because costs of care vary for individual cases, under an RPPS hospitals would be expected to make money on some patients and lose money on others so that, on average, their payments would equal their costs. This system puts hospitals at financial risk; they will lose money if they are inefficient or if they are just unlucky and receive patients who require costlier care than average.

The RPPS can provide additional payments to outlier cases, which are cases that have high costs relative to typical cases in their FRGC. Such outlier payments could reduce financial risk to hospitals and reduce financial incentives to underserve extremely high cost patients. Financial risk arises from random factors--any hospital may receive more than its share of costly cases just by chance. In addition, some hospitals may consistently receive patients that are costlier than average for their FRGC. Although other parts of the RPPS, including the case classification system and facility adjustments (disproportionate share and local wages), are intended to address systematic differences across hospitals in costs, outlier payments may also help alleviate remaining differences between a hospital's expected payment per case and the cost of efficiently treating that group of cases.

We begin below by defining a measure of financial risk which we have used to analyze such risk in the acute care PPS and which shows that, in the absence of outlier payments, financial risk could be quite large in an RPPS. Our earlier research on the acute care PPS also showed that the best way to structure an outlier policy to reduce financial risk is to use a fixed-loss policy; this policy is described in the second subsection below. Such a policy is used in the acute care PPS and we recommend it for the RPPS. The last subsection discusses the possibility of adding a low cost outlier policy to the RPPS.

Financial Risk

Rehabilitation hospitals are typically much smaller than acute care hospitals. The median freestanding rehabilitation hospital discharges only 507 Medicare cases per year and the median exempt unit discharges only 200 Medicare cases per year.[4] The median acute care PPS hospital discharged 1,117 patients in the same time frame. The smaller size of rehabilitation facilities suggests that they would be at higher financial risk from a PPS than acute hospitals--i.e., there would be a greater chance that their costs would exceed revenues by a substantial amount. However, the higher risk from their small size is partially offset by the greater homogeneity of the cost of cases within FRGCs than within DRGs.

To assess the extent of financial risk from an RPPS, we define the following measure of financial risk under a PPS for a particular hospital. Risk is defined to be the standard deviation of annual profit around its expected value expressed as a percentage of annual revenues (Keeler et al., 1988). Profit is defined as Medicare revenues minus Medicare costs. We estimate this quantity by assuming that each hospital has its own population of cases that might appear for admission and that actual cases are drawn independently from this distribution.

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[4] Calculated from the PPS 10 exempt hospital cost report file.

Let

s_i = an estimate of the standard deviation of profit across cases at hospital i,

n_i = number of annual cases at hospital i, and

r_i = average revenue per case at hospital i.

Then, under our assumption of a random draw of cases,

$$\text{Risk}_i = s_i/(\text{sqrt}(n_i)r_i).$$

Actual year-to-year variation in profits in the acute care PPS has been shown to be somewhat higher than the variation estimated from this model (Carter and Farley, 1993) due, at least in part, to management actions that affect costs or revenues.

This risk measure has several characteristics that make sense. Risk decreases with hospital size for hospitals with similar case populations. And the greater the variability of profit among cases, the greater the risk, since variability increases the chance that the hospital will receive so many unprofitable cases that it cannot offset its losses with gains.

Table 5.6 shows that, in the absence of outlier payments, the financial risk faced by the typical freestanding rehabilitation hospital under an acute RPPS would be quite similar to the amount of risk faced by the typical acute care PPS hospital in the absence of outlier payments.[5] Because exempt units are quite a bit smaller, their risk is larger--close to that of rural hospitals under the acute care PPS. Based on this table, we conclude that the need for outlier payments in an RPPS is at least as great as in the acute care PPS, where outlier payments were seen to be "a key to payment equity" (HCFA, 1987).

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[5] We restrict the analysis to payment based on MEDPAR discharges and standard weights. Because the variation in payment across payment options is small compared to the variation in case costs, we would get similar results for different payment options.

Table 5.6

Average Financial Risk in the Absence of Outlier Payments for Sample Rehabilitation Facilities, Acute Care PPS

	Average Risk
Freestanding	2.93
Exempt unit	3.24
All rehabilitation	3.19
Acute care PPS	2.89
Rural acute care PPS	3.33

SOURCE: Numbers for acute care PPS are from Keeler, Carter, and Trude (1988).

NOTE: Averages are hospital weighted rather than case weighted.

Fixed-Loss Cost Outliers

The amount of funds planned for outlier payments can be viewed as the result of a tradeoff between the need for protection for hospitals and expensive patients (which argues for more outlier payments) and the need to maintain incentives to improve efficiency (which argues for limiting outlier payments). The amount of risk protection for hospitals and patients that is purchased with each additional dollar declines as more money is spent on outlier payments. Thus, a small amount of outlier funds can have a large effect on financial risk while reducing incentives for efficiency in only a small percentage of cases. In the acute care PPS, the percentage of funds to be paid as an outlier supplement was mandated to be between 5 and 6 percent. A study that included a simulation in which the percentage of funds spent on outlier payments was expanded to 10 percent showed the expansion produced a very small decline in risk and had almost no effect on the accuracy of payments (Carter and Rumpel, 1993b). In the simulations below, we shall show that outlier payments amounting to 5 percent of total payment provide an amount of risk protection similar to that of the acute care PPS.

Given the amount planned for outlier payments, Keeler et al. (1988) show that the maximum protection from financial risk possible in a case-based outlier system[6] is achieved by use of a stop-loss insurance policy where the loss amount is equal across DRGs. Under such a policy, outlier payments are made for all cases that cost more than a threshold equal to the payment amount for the DRG plus the loss amount, where both payment and loss amount are adjusted by the facility's adjustment factor. The amount of the outlier payment is then a fraction of costs in excess of the threshold, where the fraction can be viewed as 1 minus the coinsurance amount or as the ratio of marginal cost to average cost. In the acute care PPS, such a fixed-loss outlier policy has been used since FY 1995.[7] The policy pays 80 percent of costs in excess of the threshold. We recommend that a similar policy be used for the RPPS.

LOW COST OUTLIERS

Some authors have advocated that Medicare's PPS should define short-stay outliers as cases with very short stays and pay them less than the DRG rate (e.g., Davis et al., 1990).[8] This would be fair because these patients are often less costly than average for their DRG. It would also free up funds which could then be used for additional high cost outlier payments or to increase the base DRG payment rate. Further, it would decrease the PPS incentive to unnecessarily hospitalize patients who require much less care than average for their DRG. Such short-stay outlier payments are made in the Medicaid PPSs in

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[6] Greater financial protection could be achieved via insurance against the total amount of a hospital's loss in a time period (Ellis and McGuire, 1988). However, such a policy would be much less effective than a case-based insurance policy at mitigating PPS incentives to undertreat expensive cases.

[7] To smooth the transition from previous outlier policy, day outlier payments are also being made. After September 1, 1997, the fixed-loss cost outlier policy will be the sole method used to determine outlier payments.

[8] Reducing payments for hospitals with extremely low costs also could be done with a blended hospital rate in place of a case-specific low outlier payment. This is analogous to providing the payer in a capitated payment system with protection against selection with a low cost risk corridor. However, just as hospital-level insurance would not mitigate incentives to undertreat expensive cases, a low cost adjustment at the hospital level would not mitigate the incentive for costly hospitals to admit unnecessarily. See Chapter 5 of PPRC (1995) for a discussion of pros and cons of alternative ways to share the risks involved in positive and negative selection in a capitated setting.

Iowa, Michigan, New Jersey, New York, and North Dakota.[9] In reducing payment for short-stay outliers, it is important that the reduction amount vary smoothly with LOS or cost. Otherwise, a large difference between the short-stay outlier payment and the DRG payment would introduce a strong incentive for hospitals to keep patients until they had exceeded the short-stay outlier threshold because they would receive a large change in reimbursement for the expenditure of relatively few resources.

Carter and Rumpel suggested an alternative "low cost outlier" policy in which HCFA would reduce the DRG payment by a percentage of the difference between a low cost threshold and the case's cost. Just as for short-stay outliers, this would be fairer than providing a full DRG payment for low cost cases and reduce the incentive for unnecessary admissions.[10] In addition, because the hospital would keep a fraction of the case's cost savings, it would still have an incentive to discharge the patient as soon as clinically appropriate. The first subsection below provides details of this proposal.

Implementing a low cost outlier policy in an RPPS would provide funds that could be used to increase the basic payment rate. Whether or not this is desirable depends on the distribution of costs across cases and profits across hospitals. If there are many cases with resource needs much lower than average for their FRG, if these cases are concentrated in hospitals with relatively large RPPS margins, and if funds saved by the low cost payment are then returned to hospitals in a larger FRG payment rate, the policy could improve the Medicare margins of many hospitals and improve equity among providers. The second subsection below shows that there are indeed a substantial number of very low cost cases. The simulations in Section 6 will show that low cost cases are concentrated in high profit rehabilitation facilities.

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[9] See Carter et al. (1994) for further details. In addition, Washington state defines low cost outlier cases.

[10] Because low cost outliers reduce the amount of profit from cases that are discharged much too early, there is some chance that it would even slightly reduce incentives for too early discharge. We believe that the effect would be slight because reasonable parameters of a low cost outlier policy would allow it to affect the decision in only a small portion of the cases where premature discharge is possible.

How a Low Cost Outlier Policy Would Work

The key to designing a low cost outlier policy with acceptable incentives is to avoid large discontinuities in payment that are associated with small resource expenditures. Thus, payment for low cost outlier cases should increase smoothly with cost until a low cost threshold is reached. To avoid any discontinuity in payment, reimbursement for low cost outliers should equal the FRGC reimbursement at the low cost threshold.

The payment for a low cost outlier case would be calculated as follows. First compare the estimated cost of the case, C, with the low cost threshold for the FRGC. Before the comparison, the threshold is adjusted by the facility adjustment factor. For cases with a cost less than the threshold, the total payment is reduced. To show that the payment for a case just at the threshold equals the FRGC price, we write the total payment for the case, P, as a regular FRGC payment minus a reduction in payment:

$$P = R*W*A - Z*(T*A-C)$$

where

R = the national payment rate,

W = the FRGC (or FRGCI) weight,

A = the payment factor for the hospital,

Z = the profit reduction rate (and also the rate at which payment for low cost cases increases with cost), and

T = the low cost threshold for the FRGC in standardized dollars.

The reason why we call Z the profit reduction rate is that it equals the fraction of the profit earned by keeping the costs of a case below the threshold that returns to HCFA. 1 - Z is the fraction of the profit due to below-threshold costs that is retained by the hospital. All low outlier cases earn a profit of at least $(R*W - T)*A$, which is entirely retained by the hospital.

The value of Z will be the same across all FRGCs and by design must be in the closed interval between 0 and 1. If Z exceeded 1, it would give the hospital a financial incentive to provide unneeded care until the low cost threshold was reached. If hospitals value the care they give patients, then setting Z = 1 would also provide incentives for hospitals to provide care that is of some value to the patient but not cost-effective. The value Z = 0 represents the policy of no low cost outliers.

A low cost outlier policy is defined by three characteristics: (1) the total amount of the low cost outlier payment deductions expressed as the percentage by which the basic FRGC payment would be increased to maintain budget neutrality, (2) Z, the profit reduction rate, and (3) a rule for determining the relative allocation of low cost outlier payment reductions across DRGs. The combination of these three decisions will determine the value of the threshold, T, in each FRGC.

The amount of low cost outlier payment reductions and the value of Z jointly define a policy decision that balances the costs and benefits of a low cost outlier policy. A reduction in the PPS incentives for efficient care of low cost outlier patients is a weakness of low cost outlier payments, while a reduction in incentives for unnecessary admissions is a benefit. We expect that low cost outlier payments would increase equity for providers by adjusting for differences among hospitals in the frequency of low cost cases. However, if it turns out that low cost cases are concentrated in hospitals that also have a higher-than-expected number of very costly cases, then the low cost outlier policy would decrease provider equity because it limits the ability of hospitals to offset large losses on some cases with gains on other cases. We will investigate this issue empirically in Section 6.

Given a particular low cost outlier reduction amount, the value of Z determines whether the target low cost payment reductions will come from small reductions in a lot of cases or large reductions in a small number of cases. Higher values of Z produce fewer low cost outlier cases for whom the PPS incentives for efficient care are modified. Higher values of Z also provide the least incentive for unnecessary admissions. On the other hand, lower values of Z increase the incentives for efficient care of each low cost outlier case because hospitals keep a larger share of their cost savings.

We propose thresholds so that all cases designated as low cost outliers will make a minimum standardized profit that is the same in each FRGC. The amount of the minimum profit, X, depends on the outlier pool size and value of Z. The low cost threshold for the FRGC is then given by

$$T = \text{Max}\ (R^*W - X, 0),$$

so that all cases with costs less than the FRGC payment minus the minimum profit are low cost outliers. If the value of $R^*W - X$ is negative, then the FRGC will have no low cost outliers. Given the low cost outlier pool size and the value of Z, this rule provides the maximum possible reduction in the variance of profit across cases.

How would a low cost outlier payment policy apply to transfer cases? First, the transfer per diem payment is analogous to the FRGC payment--it is set so that this set of clinically defined cases receives payment that, on average, equals costs. Thus, the transfer per diem payment is preferable to a low cost outlier reduction of the *case-level* payment and so the latter should not be considered as a payment option. However, for logical consistency, one must consider the possibility that the transfer per diem for a transfer case would result in a profit in excess of the minimum profit amount X. In this case, the transfer per diem should be reduced by the fraction Z of the profits in excess of X. This is accomplished by setting a low cost outlier threshold based on the standardized transfer per diem. So, for short-stay transfers, the low cost threshold is

$$T = \text{Max}\ (R^*W^*(\text{los} + 0.5)/\text{avelos} - X, 0).$$

Although required for logical consistency, very few transfer cases will qualify for low cost payment reductions within reasonable ranges of the payment parameters. For example, in the two policies that we simulate in Section 6, one policy had one such case and the other had 21.

Feasibility

A low cost outlier policy makes sense only if there are a reasonable number of cases that cost substantially less than the typical case in their FRGC. In many FRGCs, there are cases with profits in excess of the fixed-loss amount required to pay approximately 5 percent of payments as high cost outlier payments. Thus, a low cost outlier policy completely symmetric to the high cost outlier policy is feasible. In such a symmetric low and high cost policy, the low cost outlier threshold is set as the FRGC payment minus the fixed loss amount--just as the high cost outlier threshold is set at the FRGC payment plus the fixed-loss amount. The profit reduction rate is set equal to the marginal cost factor of 0.8. Just as the high cost outlier policy limits the loss that a hospital can receive from a few high cost cases, the low cost outlier limits the profit that can be made from a few low cost cases. We shall examine the effect of such a policy in the next section.

6. SIMULATIONS

Based on the preceding analyses, we designed a set of alternative RPPSs. Each member of the set was designed to test individual features of the RPPS and expended exactly the same amount of funds (to within one dollar per case). We simulated payment for each of these alternative RPPS under the assumption that the payment method would not affect behavior. We evaluated each simulation with respect to (1) the accuracy with which it matches payment to cost at the patient level, (2) the accuracy with which it matches payment to cost at the hospital level, (3) whether payments are close to costs for large groups of hospitals defined by specific characteristics (geographic location, type of facility, teaching hospitals, etc.), (4) whether the payments are close to cost for particular groups of patients, and (5) the financial risk associated with random variation in patient case costs.

DESIGN OF SIMULATIONS

Base Case

We begin with a base case RPPS that maximizes compatibility with the existing acute care PPS. It uses the MEDPAR discharge as the unit of payment. The FRGC payment for a discharge in hospital i in FRGC k is given by

$$F = R*A_i*W_k,$$

where R is the national payment rate, A_i is the facility payment adjustment, and W_k is the FRGC weight. In an implemented RPPS, R would be chosen to meet an expenditure target. In our case, we chose R so that total case payments (including outlier payments and transfer case payments) equal total estimated rehabilitation costs in our sample.

The weights in our base case are calculated using the standard method and are those we labeled "standard weights" in Section 3. The payment factor was derived in Section 4 and is equal to

$$A_i = \exp(0.448*\log(\text{wageindex}) + 0.803*\text{Medicaid}),$$

where wage index is the acute hospital wage index for the metropolitan area or rural area of the state containing the hospital, and Medicaid is the fraction of the hospital's Medicare cases that are eligible for Medicaid.

The simulated payment includes a fixed-loss outlier policy with the loss threshold, L, chosen so that 5 percent of total payments would be made as outlier supplements. The outlier threshold for a case in hospital i in FRGC k is calculated as

$$T_{ik} = R*A_i*W_k + L*A_i.$$

The cost of the case, C, is estimated by multiplying the charges for the case by a cost to charge ratio calculated from the hospital's most recent available cost report. If this cost exceeds T_{ik}, then the case receives an outlier payment which is added to the FRGC payment:

$$OUT = 0.8*(C - T_{ik}).$$

The recommended transfer policy was used. Each transfer case receives the minimum of the FRGC payment and a per diem payment equal to the FRGC payment divided by the arithmetic LOS plus one-half day per diem, which accounts for the fixed costs of the case.

The base case contains no low cost case payment adjustments.

Alternative Payment Systems

Three of the alternative RPPS that we evaluate here are based on using different weights (see Table 6.1). We use the UDSmr case as the basis of payment, and then use the "UDSmr case weights" that are calculated using the standard method and hospital payment factors based on this unit of payment.

We chose to simulate the HSRV weights because, in our analysis in Section 4, these appeared to be the least compressed. We also simulate fair weights because these might provide more accurate total payment--i.e., including outlier payments. In both cases, we use the hospital payment factors from the base case. As seen in Section 4, the relationship among payment factors and hospital costs is insensitive to the details of the weight methodology.

Table 6.1

Design of Simulation Runs

Simulation Option (Name of Simulation)	Unit of Payment	Name of Weight	Low Cost Outlier, %	High Cost Outlier, %
Base case	MEDPAR discharge	Standard	0	5
UDSmr case	UDSmr case	UDSmr	0	5
HSRV weights	MEDPAR discharge	HSRV	0	5
Fair weights	MEDPAR discharge	Fair weights	0	5
Low cost 1	MEDPAR discharge	Standard	0.725	5
Low cost 2	MEDPAR discharge	Standard	1.5	5
No outlier	MEDPAR discharge	Standard	0	0

NOTE: All simulations except no outlier policy pay 5 percent of payment to high cost outliers and use recommended transfer policy.

Two of the alternatives are just like the base case except that they reduce payment amount for very low cost cases using the algorithm defined in Section 5. The first of these alternatives uses a low cost outlier policy that is completely symmetric to the high cost outlier policy.

The minimum profit for cases subject to a low cost outlier payment reduction, X, is set equal to the high cost fixed loss amount, L. In this policy, the low cost outlier threshold for an FRG is set at

$$LCT_{ik} = R*A_i*W_k - X*A_i.$$

Just as for a high cost outlier, the cost of the case, C, is estimated by multiplying the charges for the case by a cost to charge ratio calculated from the most recent available cost report. If this cost is less than LCT_{ik}, then the FRGC payment is reduced by the low cost outlier amount:

$$LCOUT = 0.8*(LCT_{ik} - C).$$

It turns out that in our sample, this results in the sum of LCOUT across all cases being equal to 0.725 percent of total payments. The second simulated low cost outlier policy is similar except that it uses a smaller value for X, the minimum profit for cases subject to a low cost outlier payment reduction. This smaller X results in higher values of the low cost outlier thresholds, more low cost outlier cases, and higher values of LCOUT. We chose a value for the minimum profit so that the sum of LCOUT would be about double the value from the first low cost outlier run.

All five of these alternatives use the same outlier payment policy and outlier expenditure target as the base case. To estimate the effect of outlier payments in an RPPS, we also simulated a policy like the base case except that it did not provide high cost outlier payments. All simulations use the same transfer payment method.

We could not simulate existing TEFRA payments because cost report data contemporaneous with our case data were not available.

The parameters of each simulation are shown in Table 6.2 along with the resulting average per case values for total payment, outlier payment (OUT), and low cost outlier reduction (LCOUT). The outlier payments are averaged over all cases, not just outlier cases. As shown in Table 6.2, the rates and outlier thresholds that we used achieved total payment per discharge very close to cost per discharge for the base case and all

Table 6.2

Simulation Parameters and Payment Amounts

Simulation	Federal Rate	Fixed-Loss Amount	Low Cost Outlier Max. Profit	Per Case Payment		
				Total	Outlier	Low Cost Reduction
Base case	12,074	8,950	---	13,075.00	653	0
UDSmr case	12,218	9,067	---	13,483.47	671	0
HSRV weights	12,080	8,825	---	13,074.93	652	0
Fair weights	12,080	8,825	---	13,074.96	652	0
Low cost Outlier 1	12,167	8,850	8,850	13,075.15	652	95
Low cost Outlier 2	12,265	8,735	7,040	13,074.92	652	196
No outlier	12,708	---	---	13,074.61	0	0

NOTE: Average cost per MEDPAR discharge for the sample was 13,074.96 and cost per UDSmr case was 13,483.59.

discharge simulations and total payment per UDSmr case very close to cost per UDSmr case. The parameters also resulted in 5.0 percent of payments being paid as high cost outlier payments in all cases. The different unit of payment between the base case and the UDSmr case requires a noticeably different national rate to maintain budget neutrality. The interaction between weights and standardization factor also requires that the federal rate and the fixed-loss threshold for high cost outliers vary slightly among the per discharge simulations.

RESULTS

Fit of Payments to Cost

To test the accuracy of the fit of payments to cost at the case level, we ran a univariate regression of the log of the cost of each case on the log of the total payment amount for the case (including outlier payments). Table 6.3 shows the results. The payment formula for the base case accounts for almost half of the case-level variation in costs. The last line of the table shows that outlier payments are an important reason for this high R-square. In the absence of outlier payments, the FRGC payment formula would explain only 38.8 percent of the variance in cases.

The HSRV weights and the fair weights do just as well as the base case in explaining discharge-level costs. The UDSmr case simulation explains slightly less of the variance in cost per UDSmr case than the

Table 6.3

Accuracy of Match of Cost to Payment at the Discharge (Case) Level

	Regression of Log (Cost) on Log (Payment)			
Simulation	R-Square	constant	coef.	t-stat
Base case	0.485	-0.341	1.0237	305.4
UDSmr case	0.459	-0.331	1.0228	285.1
HSRV weights	0.486	-0.116	1.0003	305.8
Fair weights	0.485	-0.102	0.9988	305.2
Low cost outlier 1	0.513	-0.721	1.0640	323.1
Low cost outlier 2	0.540	-1.065	1.1004	341.4
No outlier	0.388	-0.044	0.9897	250.5

other simulations explain about the variance in cost per discharge. Since the low cost outlier policies match payment to cost better for the very low cost cases, they explain the variation in cost at the case level better.

Earlier we discussed the possibility that weights are compressed--i.e., that weights for high cost cases are lower than they should be. However, the proportionality between costs and payments is indistinguishable from 1 for both the HSRV weights and the fair weights. Although one can statistically distinguish the coefficient on the log of the payment from 1 in the other simulations, the difference from 1 is quite modest in all cases but the low cost outlier simulations. The reason for the larger coefficients in the low cost outlier simulations is that low cost outliers are concentrated in high weight FRGCs and, thus, cases in high weight FRGCs are underpaid in these simulations. This could be fixed by using a fair weight algorithm in combination with low cost outliers.

Table 6.4 provides similar regressions of the cost per case on the hospital level. Here the base case (and using each of the weight methodologies) explains roughly 60 percent of the variance in costs across hospitals. This is not much different than the results of the acute care PPS. In the acute PPS, the correlation coefficient between per case costs and reimbursements at the hospital level was reported at 0.82, with an implied R-square of 0.67 (Carter and Rumpel, 1993b).

Outlier payments are even more important at the hospital level than at the case level. Adding outlier payments increases the percentage of the variance in hospital-level costs explained by the RPPS payments from 36.4 percent to 60.4 percent. We could not find a similar number for the acute PPS.

Low cost outlier payments noticeably improve the match of costs to payment at the hospital level. This shows that these low cost cases are not randomly distributed across hospitals but concentrated at some hospitals that would, in the absence of low cost outlier payment reductions, make more than the costs.

The coefficient on the payment in Table 6.4 is quite far from 1.0. However, these data are *not* due to the standard model of CMI compression

Table 6.4

Accuracy of Match of Cost to Payment at the Hospital Level

	Regression of Log (Cost) on Log (Payment)			
Simulation	R-Square	Constant	coef.	t-stat
Base case	0.604	-3.093	1.322	22.75
UDSmr case	0.614	-2.990	1.310	22.23
HSRV weights	0.596	-2.745	1.285	22.36
Fair weights	0.603	-2.810	1.292	22.68
Low cost outlier 1	0.624	-3.410	1.355	23.77
Low cost outlier 2	0.649	-3.679	1.384	25.06
No outlier	0.364	-1.558	1.161	13.94

wherein high cost cases are undervalued and low cost cases are overvalued, leading to hospitals with high CMIs receiving payments that are too low and hospitals with low CMIs receiving payments that are too high. Table 6.5 divides hospitals according to their quartile of the standard method CMI. It shows that there is a curvilinear relationship between the CMI and the ratio of payments to cost. The hospitals with the lowest CMI have the highest ratio of payments to cost, as expected. However, the lowest ratio of payment to cost is found in the second quartile of the CMI. The hospitals with the highest CMI are actually paid an amount very close to their costs by each of the simulations.

Outlier Payments

We have seen that both high and low cost outlier payments greatly increase the accuracy of the RPPS. In this subsection, we look more closely at the kinds of cases and hospitals that receive outlier payments and the effect of high cost outlier payments on reducing risk. Because the results are similar across the simulations, we restrict the data on high cost outliers to the base case.

Tables 6.6 and 6.7 show that the high and low cost outlier policies are working as intended. Table 6.6 shows that roughly 9 percent of discharges receive a high cost outlier payment. This is much higher than for the acute care PPS because the distribution of costs per case is tighter for FRGCs than for DRGs. However, just as for the acute care PPS, outlier cases cause significant losses to the hospital--payments, including outlier payments, cover only 68.1 percent of the costs of the

Table 6.5

Payment to Cost Ratios by CMI Quartile, Under Alternative PPS Designs

CMI Quartile	No. of Hospitals	No of MEDPAR Discharges	Payment-to-Cost Ratio						
			Base Case	UDSmr Case	HSRV	Fair Weights	Low Cost 1 Outlier	Low Cost 2 Outlier	No Outlier
Lowest CMI	85	33,892	1.062	1.060	1.057	1.057	1.065	1.065	1.074
Second	86	28,595	0.947	0.947	0.945	0.947	0.949	0.951	0.944
Third	85	22,199	0.980	0.981	0.982	0.982	0.979	0.978	0.978
Highest CMI	86	14,416	1.018	1.021	1.027	1.025	1.013	1.009	1.007

Table 6.6

Outlier Payments in the Base Case

		Average			
Type of Case	N	Outlier Payment	Cost	Total Payment	Ratio
Outlier	9,174	7,051	33,000	22,487	0.681
Non-outlier	89,928	0	11,042	12,115	1.097
Total	99,102	653	13,075	13,075	1.000

Table 6.7

Low Cost Outlier Payments

Type of Case	N	Payment Reduction	Cost	Total Payment	Ratio
Low Cost 1					
Low cost outlier	4,089	2,295	6,820	16,614	2.436
Not low cost outlier	95,013	0	13,344	12,923	0.968
All cases	99,102	95	13,075	13,075	1.000
Low cost 2					
Low cost outlier	8,222	2,358	7,140	15,006	2.102
Not low cost outlier	90,880	0	13,612	12,900	0.948
All cases	99,102	196	13,075	13,075	1.000

average outlier case.[1] Despite the large number of outlier cases, all of them cause substantial loss. The 95th percentile of the payment to cost ratio for outlier cases is 0.853. Note that payments are not intended to cover the full cost of these outlier cases--merely to limit the loss so that an efficient hospital can match the loss with profits from profitable cases.

Table 6.7 shows that payment reductions in both low cost simulations go to very profitable cases. In the first simulation, when the low cost outlier threshold is set to be the mirror image of the high cost outlier threshold, payment is reduced for about 4 percent of the cases. The average amount of the reduction is $2,295 per case. But these cases receive so few resources in the hospital that they still receive a payment equal to 2.436 times cost. In the second low cost outlier simulation, the profit threshold is moved down from 8,850 to 7,040 (see Table 6.2). This small change in the profit threshold doubles the number of cases that receive a profit reduction. However, these cases remain extremely profitable after receiving the reduced payment.

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[1] In the acute PPS, the operating payment to cost ratio for outlier cases was estimated at 66 percent (Carter and Farley, 1993).

Table 6.8 shows that, as we would hope, high cost outlier payments are concentrated in hospitals that are paid less than cost. Although the amount of concentration is smaller, low cost outlier payments are concentrated in hospitals that will make a substantial profit under an RPPS. The profit quartile for each hospital was determined from its payment to cost ratio in the base case.

Table 6.9 shows that outlier payments provide substantial protection for hospitals from the financial risk of an RPPS. In the base case, the standard deviation of annual profit is 2.42 percent of annual revenues. This is slightly below the risk found in the acute care PPS, which was calculated as being 2.64 percent from the initial outlier policy and 2.47 percent from a similar fixed-loss policy.

Patient Categories

Table 6.10 shows payment to cost ratios for groups of patients from our simulations. The first two lines show that our short-stay transfer policy results in payments very close to costs in all of the simulations. Even though many fewer UDSmr cases than MEDPAR discharges are paid as transfers, the same transfer policy appears to work for simulations using both units of payment.

Despite the special modeling of interrupted stays that we used when the UDSmr case is the unit of payment, treating each part of an interrupted stay as a separate discharge for payment actually results in slightly more accurate payment than one gets from the model. The payment to cost ratios are almost identical for the base case and the UDSmr case for each of the other patient categories.

In all simulations, payments are roughly proportional to costs within each of the three other patient groups in the table:

Table 6.8

Relationship Between Hospital's Profit Quartile and High and Low Cost Outlier Payments

				Outlier Payment			Payment Reduction		Payment to Cost Ratio			
Profit Quartile	Hospital	Cases	Cost	Base	LC1	LC2	LC1	LC2	No Outlier	Base	LC1	LC2
1	86	24834	18149	1672	1670	1670	59	112	0.728	0.784	0.786	0.789
2	82	22634	13933	591	590	593	72	142	0.954	0.949	0.951	0.953
3	87	23604	11741	324	324	323	99	200	1.121	1.092	1.092	1.092
4	86	28030	9010	76	76	76	141	310	1.410	1.348	1.342	1.334
All	341	99102	13075	653	652	652	95	196	1.000	1.000	1.000	1.000

Table 6.9

Risk Reduction Achieved by High Cost Outlier Payments

	Standard Deviation of Profit on a Percentage of Revenue		
	No Outlier	Base Case	% Reduction
Mean	3.19	2.42	24.1
25th percentile	1.98	1.72	13.1
Median	2.74	2.23	18.6
75th percentile	3.87	2.91	24.8

comorbidities, gender, and age. Although a male patient typically costs 10.8 percent more than a female patient,[2] and sex is not explicitly accounted for in this payment system, the FRGCs and other elements manage to reflect these cost differences quite well. Similarly, younger patients cost much more than older ones and age has only a tiny explicit effect on case classification, but their payment to cost ratios are very close.[3]

Hospital Characteristics

Table 6.11 shows payment to cost ratios for various groups of hospitals from each of our simulations. There is very little difference across simulations in the treatment of any group of hospitals. There are, however, noticeable differences in the treatment of certain groups of hospitals within each simulation.

There are only small differences between urban and rural hospitals. The rural hospitals in our sample receive little more than 96 percent of their costs as payment. The best-paid group is the smaller urban areas (payment = 102 percent of costs), which are lumped with rural areas in the acute care PPS. A separate payment rate for large urban areas does not appear to be needed in an acute RPPS.

The differences among types of providers are somewhat larger--freestanding facilities receive only 95 percent of costs while exempt units receive about 105 percent of costs. However, the picture is

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[2] Average per case costs for men and women are $13,912 and $12,553.

[3] Average per case costs for the three age groups in the table are $14,747, $13,075, and $12,716, so that the youngest group costs 16 percent more than the oldest group.

Table 6.10

Payment to Cost Ratios for Groups of Patients Under Alternative Scenarios

		Payment-to-Cost Ratios						
Patient Group	No. of Discharges	No. of Cases	Base Case	UDSmr Case	HSRV	Fair Weights	Low Cost Outlier 1	Low Cost Outlier 2
All	99,102	95,744	1.000	1.000	1.000	1.000	1.000	1.000
Short-stay transfer	6,459	3,924	0.977	0.962	0.986	0.987	0.985	0.992
Nontransfer	92,643	91,820	1.001	1.001	1.001	1.000	1.001	1.000
Interrupted stay	6,313	2,955	1.017	1.046	1.003	1.024	1.011	1.007
Not interrupted	92,789	92,789	0.999	0.997	0.999	0.999	0.999	1.000
With comorbidity	20,721	19,646	0.995	0.999	0.999	0.999	0.992	0.989
Without comorbidity	78,381	76,098	1.002	1.003	1.003	1.002	1.003	1.004
Female	60,965	59,171	0.998	0.997	0.995	0.996	0.999	1.000
Male	38,041	18,908	1.003	1.004	1.007	1.006	1.001	1.000
< 65 years	7,388	7,089	0.977	0.979	0.976	0.979	0.973	0.971
65-79	57,270	55,258	0.999	1.000	1.001	1.000	0.999	1.000
80+	34,348	33,303	1.007	1.006	1.004	1.006	1.008	1.008

Table 6.11

Payment to Cost Ratios for Groups of Hospitals Under Alternative PPS Designs

Hospital Group	No. of Hospitals	No. of MEDPAR Discharges	Payment-to-Cost Ratios Base Case	UDSmr Case	HSRV	Fair Weights	Low Cost 1	Low Cost 2
All	341	99,102	1.000	1.000	1.000	1.000	1.000	1.000
Rural	51	13,281	0.964	0.963	0.963	0.964	0.964	0.965
Large urban	135	40,825	0.990	0.990	0.989	0.989	0.990	0.990
Other urban	155	44,996	1.022	1.021	1.022	1.022	1.021	1.021
Freestanding	97	46,649	0.951	0.950	0.947	0.950	0.951	0.952
Exempt unit	232	49,018	1.056	1.057	1.059	1.056	1.055	1.054
LTC	12	3,435	0.965	0.959	0.969	0.966	0.964	0.965
Certification Year								
Up to 84	135	48,242	1.052	1.053	1.054	1.052	1.051	1.050
85 to 89	113	28,492	1.013	1.013	1.012	1.013	1.013	1.013
90 or later	93	22,368	0.895	0.895	0.893	0.895	0.896	0.898
Type and Year								
Freestanding								
Up to 84	29	21,665	1.069	1.069	1.067	1.067	1.071	1.071
85 to 89	29	10,768	0.927	0.926	0.923	0.928	0.927	0.927
90 or later	39	14,216	0.841	0.841	0.838	0.842	0.843	0.845
Unit								
Up to 84	98	23,762	1.054	1.057	1.059	1.056	1.052	1.050
85 to 89	82	17,321	1.081	1.081	1.083	1.080	1.082	1.081
90 or later	55	7,935	1.010	1.010	1.011	1.010	1.011	1.012

Table 6.11--continued

Hospital Group	No. of Hospitals	No. of MEDPAR Discharges	Payment-to-Cost Ratios					
			Base Case	UDSmr Case	HSRV	Fair Weights	Low Cost 1	Low Cost 2
LTC								
Up to 84	8	2,815	0.935	0.931	0.939	0.937	0.935	0.936
85 to 89	2	403	1.064	1.062	1.072	1.066	1.064	1.063
90 or later	2	217	1.259	1.239	1.259	1.257	1.256	1.253
Teaching								
None	255	70,228	1.002	1.002	1.002	1.002	1.002	1.001
Minor	76	27,464	0.993	0.994	0.994	0.992	0.995	0.996
Major	10	1,410	1.019	1.020	1.026	1.022	1.020	1.019
Percent Medicaid								
< 5	86	25,003	1.012	1.011	1.010	1.009	1.015	1.017
5 - 14.9	182	57,744	1.007	1.007	1.008	1.007	1.008	1.007
≥ 15	73	16,355	0.966	0.968	0.968	0.970	0.963	0.961
Medicaid and Teaching								
< 5% Medicaid, no teaching	65	16,424	0.991	0.988	0.987	0.988	0.993	0.994
< 5% Medicaid, teaching	21	8,579	1.057	1.060	1.058	1.054	1.061	1.064
5-14% Medicaid, no teaching	131	40,389	1.008	1.008	1.008	1.008	1.008	1.008
5-14% Medicaid, teaching	51	17,355	1.006	1.006	1.007	1.005	1.007	1.006
> 15% Medicaid, no teaching	59	13,415	0.999	1.000	1.000	1.002	0.994	0.992
> 15% Medicaid, teaching	14	2,940	0.841	0.842	0.845	0.843	0.841	0.842

NOTE: Payment and cost values used in ratios are case weighted. Major teaching hospitals are those with more than 0.25 interns and residents per bed.

actually more complicated than this, as the next section of the table shows. Hospitals that have been under TEFRA since the earliest PPS years make a 5 percent profit while the newest hospitals see a substantial loss. As we discussed earlier, these hospitals have not felt nearly as much pressure to control costs as the other hospitals, and those still establishing a baseline have a clear incentive to increase costs. There is almost no difference between the freestanding hospitals and exempt units that had baselines established in the earliest period. Within each group of hospitals, the payment to cost ratio declines with an increase in the year of certification, although the decline is somewhat steeper for freestanding hospitals than for exempt units.

Even though our payment system takes no explicit account of teaching hospitals, the payment system appears quite fair on this dimension. As we discussed in Section 2, our data on the magnitude of the teaching program may be flawed.

Despite the extra payments given to hospitals with Medicaid patients, there remains a small bias against the average hospital that has more than 15 percent of their Medicare patients being Medicaid eligible. As the last section of Table 6.11 shows, this result is due to a small number of teaching hospitals that have a high percentage of Medicaid cases. Since nonteaching hospitals with a high percentage of Medicaid cases have payment to cost ratios near 1, we believe that the relationship between costs and percentage of Medicaid eligible is linear as we have modeled it.[4] There remain two possible explanations. Data problems may have hidden the extra costs due to teaching hospitals, and if these were reimbursed, the hospitals would find most of their costs covered. An alternative explanation is that these are hospitals in inner city areas and they incur higher costs related to the location of the facility rather than to either teaching or their Medicaid patients.

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[4] Residual plots from the regressions in Section 4 also suggest a linear relationship.

7. MONITORING

The greater cost control incentives from an RPPS might result in too early discharge of some cases, producing either quality of care problems, increased Medicare expenditures for additional care, or both. The evidence from the acute care PPS suggests that problems arising from shortened LOS can be more than a theoretical worry. LOS declined dramatically with the introduction of the acute care PPS, and an increased number of cases with medical instability at discharge was the only sign of poor care detectable after the introduction of the acute care PPS (Kahn et al., 1990; Coulam and Gaumer, 1991). The expected size of the change in LOS in an RPPS should be smaller than that seen in the introduction of the acute care PPS, however, because hospitals already can retain some of the savings from increased efficiency under TEFRA. On the other hand, the TEFRA incentives may mean that some hospitals already discharge cases prematurely, so that, e.g., SNF care is required before the patient returns to the community. In addition, the acute care PPS and TEFRA both provide financial incentives for admission of patients who are not medically ready for inpatient rehabilitation and are discharged from the rehabilitation facility without receiving a full course of treatment and who may return for a readmission, thus incurring extra Medicare expenditures. These incentives would remain under an RPPS, although including a short-stay outlier policy would mitigate the incentives for unnecessary admissions from the point of view of the rehabilitation facility, but not the acute care hospital.

In this section, we examine the possibility of using two outcomes to monitor whether a decline in LOS affected the quality of care: functional status at the time of discharge and whether the patient resides in a SNF within 30 days of discharge from rehabilitation. For each outcome, we investigate the ability of the FIM and/or FIM/FRGs to be the basis of risk adjustment for developing a hospital index and the extent to which there are differences across hospitals in risk-adjusted outcomes. The risk-adjustment equations that we present were aimed at determining the feasibility of constructing hospital-level indices. We do not present them as optimal risk-adjustment models. It is quite likely that they could be significantly improved with additional effort.

FUNCTIONAL GAIN AT DISCHARGE

One result of too early discharge is that the patient may not achieve the functional independence that would be expected given his clinical status and impairment. In this subsection, we ask if it is feasible to build an index for each hospital showing how its patients' functional gain compares to the national average gain for similar patients. Such an index could be used in conjunction with monitoring changes in LOS. It also could be used by hospitals for self-monitoring of their own performance.

We examine gain rather than discharge status for several reasons. We do not wish to penalize hospitals that accept difficult cases with low initial scores and that provide substantial gains to their patients even if their impairment limits them to less than total function at discharge. We also do not wish to reward hospitals that accept patients who are functioning near the top of the scale at admission and who did not really need inpatient rehabilitation. Although the regression to the mean phenomenon will affect individual gain scores, we expect that it will have a relatively small effect on a hospital-level index.

Method

We predicted the FIM improvement separately for each RIC using the UDSmr case as our unit of analysis. We modeled the improvement in FIM score during rehabilitation by regressing change in FIM score between admission and discharge on patient characteristics.

We deleted unusual cases, including all cases ending in death or transfer. We eliminated the four RICs with fewer than 500 cases in our sample. We found that for 1385 patients (1.5 percent), onset of the condition causing the rehabilitation stay was reported as one day or less. Because less than 24 hours between condition onset and rehabilitation admission did not seem plausible, these cases plus six cases with invalid onset dates were excluded from the model specifications, resulting in 88,444 cases for the analysis.

We examined each of the following independent variables: admission FIM motor score, admission FIM cognitive score, length of time since onset of the condition, age, gender, Medicaid status, presence of comorbidity, whether an interruption in stay (for an inpatient hospitalization) occurred, and whether the stay was a readmission. Admission FIMs, age, and onset delay were categorized for the regression models. Table 7.1 shows the categories used for the three largest RICs. The omitted categories used for comparison are motor score of 86 or higher, a cognitive score of 31 or higher, age of 95 or older, and onset of eight or more weeks before admission (six or more weeks for hip fracture and hip replacement). Slightly different categorizations were used for some of the RICs because of smaller sample sizes, RIC-specific differences in age distribution, and the frequency with which readmissions occurred.

In preliminary analysis, we entered all the variables in each RIC and then dropped patient characteristics that were not significant ($p > 0.05$). The selected models for the three largest RICs are shown in Table 7.1. The coefficients for the interaction of readmission status and onset include the readmission main effect.

We tested whether FRG could substitute for FIM score and found a substantial reduction in power. Separate models that added the total cost of the stay or the total length of stay to the selected model also were constructed to determine the relationship between FIM gain and resource use.

Using the selected models, predicted values of FIM improvement were produced for each individual stay (because of different specifications across RICs, eight different models were used to produce predicted values). An index that averaged the difference between the actual and the predicted FIM improvement (the residuals) for each individual was generated to compare FIM improvement across hospitals. A separate index was calculated for stroke, for hip fracture, for hip replacement, for the remaining RICs, and for all RICs together.

We examined the distribution of the index values across rehabilitation facilities. To determine how likely it was that all rehabilitation facilities would produce the same gain for the same

Table 7.1

Regression Coefficients for FIM^{SM} Improvement Models with Significant Variables Only, by RIC (RICs 1, 7, 8)

	Stroke (RIC 1)		Hip Fracture (RIC 7)		Hip Replacement (RIC 8)	
Variable	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Constant	-8.57	-3.47	-2.72	-1.10	-11.68	-3.93
Motor FIM ≤15	16.32	8.30	18.24	6.76	23.04	6.82
16 to 20	20.44	10.50	17.22	6.84	28.04	9.28
21 to 25	23.47	12.12	19.04	7.91	25.36	8.99
26 to 30	25.18	13.03	20.85	8.83	26.20	9.45
31 to 35	25.81	13.36	23.02	9.81	28.41	10.37
36 to 40	25.82	13.38	23.29	9.96	28.56	10.48
41 to 45	25.65	13.30	22.60	9.69	27.45	10.11
46 to 55	23.80	12.39	20.35	8.75	24.41	9.00
56 to 65	19.46	10.10	15.53	6.67	18.90	6.97
66 to 75	14.44	7.39	9.15	3.85	12.14	4.47
76 to 85	6.97	3.36	na	na	4.59	1.66
Cognitive FIM ≤ 6	-1.46	-3.37	1.29	1.66	-1.12	-1.59
7 to 9	0.75	1.83	-7.84	-8.16	-7.89	-5.96
10 to 15	1.30	4.57	-5.01	-10.37	-1.37	-2.08
16 to 20	0.90	3.35	-2.82	-7.51	-1.61	-3.35
21 to 25	0.95	3.74	-1.74	-6.07	-0.43	-1.49
26 to 30	0.92	3.74	-0.56	-2.51	0.38	2.03
Male	0.58	3.74	na	na	na	na
Age ≤ 50	8.12	5.62	5.93	5.22	7.03	5.80
51 to 64	7.76	6.17	5.68	6.42	8.79	8.12
65 to 74	7.72	6.41	5.76	8.57	9.17	8.83
75 to 84	5.15	4.29	4.86	7.41	8.58	8.28
85 to 94	2.29	1.89	3.40	5.14	6.82	6.51
Onset 2 days	na	na	1.51	1.43	4.36	5.20
3 days	na	na	2.37	2.96	4.48	6.45
4 days	na	na	1.78	2.50	4.57	6.72
5 days	na	na	1.93	2.80	4.13	6.09
6 days	na	na	1.40	2.06	3.98	5.88
7 days	na	na	0.80	1.17	4.06	5.97
First week	3.64	3.67	na	na	na	na
Second week	2.60	2.62	0.81	1.25	3.29	4.90
Third week	2.13	2.11	0.14	0.21	2.02	2.74
Fourth week	1.37	1.32	0.15	0.19	1.19	1.14
Fifth week	0.49	0.45	-0.63	-0.66	0.20	0.21
Sixth week	0.57	0.51	na	na	na	na
Seventh week	0.12	0.10	na	na	na	na
Readmission*onset						
2 days	na	na	-2.18	-0.79	-1.88	-0.89
3 days	na	na	-4.88	-2.31	-0.85	-0.93
4 days	na	na	-3.38	-2.22	-0.49	-0.77
5 days	na	na	-1.07	-0.88	-0.01	-0.03
6 days	na	na	-1.69	-1.36	-0.36	-0.55
7 days	na	na	-0.65	-0.53	-1.96	-2.61

Table 7.1--continued

	Stroke (RIC 1)		Hip fracture (RIC 7)		Hip replacement (RIC 8)	
Variable	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
Readmission*onset						
First week	-3.81	-5.64	na	na	na	na
Second week	-3.90	-5.28	-1.40	-2.11	-0.95	-1.77
Third week	-3.76	-3.11	-3.58	-2.79	-0.10	0.08
Fourth week	-4.08	-2.46	-1.81	-1.00	-0.31	-0.15
Fifth week	-2.01	-1.05	3.34	1.37	-7.36	-2.61
Sixth week	-2.42	-0.89	-5.71	-3.24	1.73	0.90
Seventh week	-5.39	-2.40	na	na	na	na
Longer	-7.46	-2.56	na	na	na	na

NOTE: R-square for the models are 0.10, 0.11, 0.29; for RIC 8, cases with onset greater than 60 were excluded from model.

patient, the index values were transformed to a standard normal (0,1) distribution. Descriptive statistics including the mean and standard deviation were used to describe the distribution of FIM improvement for each hospital. Facility-level distributions across each of the five indices were produced.

Results

The variance explained for the 17 RICs modeled ranged from 10 percent to 37 percent (see Table 7.2). Motor and cognitive scores at admission were stronger predictors of total FIM improvement in all RIC groups compared to FRGs.

The admission cognitive and motor FIM scores were expected to be associated with lower FIM change for the lowest and highest admission FIM scores, because these cases represented the sickest and the highest functioning patients. In all RICs, FIM improvement increased with higher admission FIM scores and then declined, as expected. The curves were quite smooth, as illustrated in Table 7.1 The smoothness was, in part, a result of our changing the width of FIM categories to maintain adequate sample size. Readmission was a statistically significant predictor of FIM change for all RICs. Readmission was negatively correlated with FIM improvement.

Time since onset of the condition was associated with FIM improvement in all RIC categories, with greater FIM improvement in cases

Table 7.2

Variance Explained in FIM Improvement by Model Specifications

	R-Square for Model					
	All Variables		Significant Variables Only			
RIC	FIM Scales	Only FRG	FIM Scales[a]	Only FRG	FIM Scales and Cost	FIM Scales and LOS
1	10	6	10	6	15	14
2	24	21	23	20	28	30
3	10	8	10	8	13	15
4	29	27	28	27	31	33
5	14	11	14	11	15	15
6	10	8	10	8	13	12
7	11	8	11	8	13	14
8	29	25	29	25	29	29
9	13	9	13	9	15	15
10	28	22	28	22	30	29
11	23	17	23	17	24	24
12	19	13	19	13	21	22
14	22	17	22	16	22	23
15	28	17	27	15	30	30
16	38	23	37	23	37	38
18	10	9	10	8	12	12

[a] Selected model.

that were 7 to 14 days post onset and then declining improvement or no significant association with FIM improvement. Generally FIM improvement declined with age.

Gender was a statistically significant predictor of FIM improvement in only three RIC categories: stroke, cardiac, and pain syndrome patients.

Medicaid status was associated with FIM improvement in only four models. Medicaid status predicted lower FIM improvement for stroke patients, for cardiac patients, for patients with pulmonary conditions, and for patients with traumatic brain injury. It may be that Medicaid patients with these conditions are generally sicker, or perhaps they just receive fewer services. In other RICs, Medicaid was not a statistically significant predictor of FIM improvement and the sign of the coefficient varied. It is not clear why these relationships were found and more detailed examination of these trends is warranted.

The comorbidity variable used in this analysis was a statistically significant predictor of lower FIM improvement in pulmonary and pain syndrome patients; if these relationships occurred by chance, we would have expected a statistically significant relationship in one of the RICs analyzed, so this may be simply due to chance. Interrupted stay was also a statistically significant, negative predictor of FIM improvement in two RICs--amputation and cardiac.

Final cost of the stay was a significant and positive predictor of FIM improvement in all RIC categories. Length of stay also was a significant and positive predictor of FIM improvement for all RIC categories. Thus, holding all other variables constant, both increased cost and longer length of the rehabilitation stay produce higher FIM improvement. (See Table 7.3.)

Facility Analysis

Results of the hospital-level analyses revealed that hospitals do not perform equally in producing FIM improvement. If all hospitals had a similar distribution in FIM improvement in their patients, we would expect that across all hospitals the mean difference between actual and predicted FIM improvement would be normally distributed with a mean of zero. However, for all of the indices, there were larger numbers of hospitals with high FIM improvement index scores and of hospitals with low FIM improvement index scores than would be expected by chance alone.

We present the analyses in each clinical category only for hospitals with 10 or more cases in that category. As shown in Table 7.4, 20.5 percent of hospitals had significantly better than expected FIM gain for stroke, as indicated by a Z score higher than 1.645. If all hospitals performed equally well, only 5 percent of hospitals would be expected to do this well by chance. There were also many hospitals with worse than expected performance: 24.1 percent of hospitals had a Z score lower than -1.645, as compared to the 5 percent that would be expected by chance alone. When all RIC categories were combined, 29.6 percent of hospitals had Z scores higher than 1.645, as compared to the 5 percent expected, and 33.1 percent had Z scores lower than -1.645. On average, larger hospitals had better performance than smaller hospitals, leading to a hospital weighted mean that was less than zero. The distribution was roughly symmetric around the mean, although somewhat skewed to the left for the orthopedic RICs. The distribution did not

Table 7.3

Coefficients on Cost and Length of Stay in Models of FIM Improvement, Controlling for Admission FIM, Age, Onset, and Readmission

	LOS Model		Final Cost Model		
RIC	coef.	t-stat	coef.	t-stat	Mean FIM Improvement
1	0.264	41.12	0.000298	37.08	23.73
2	0.306	9.91	0.000357	9.02	26.30
3	0.288	10.26	0.000271	8.06	23.38
4	0.155	6.45	0.000164	5.05	19.21
5	0.110	6.22	0.000117	5.07	21.50
6	0.172	10.21	0.000248	11.08	19.59
7	0.201	20.56	0.000257	19.18	22.02
8	0.077	8.48	0.000095	7.22	22.40
9	0.166	9.37	0.000209	8.41	21.41
10	0.134	4.68	0.000231	5.45	20.52
11	0.146	4.99	0.000187	4.90	19.74
12	0.159	11.95	0.000156	9.59	18.10
14	0.161	5.76	0.000097	2.95	22.55
15	0.144	7.63	0.000134	7.37	20.23
16	0.060	1.93	0.000052	1.31	18.92
18	0.134	8.47	0.000157	8.68	20.75

NOTE: Models for RICs 1, 14, and 16 also control for gender. R-Squares were shown in Table 7.2.

Table 7.4

Distribution of Normal Transformation of Mean FIM Improvement Across Rehabilitation Facilities

RIC	Hospitals (N)	Percent Facilities with Z < -1.645	Percent Facilities with Z > 1.645	(Actual - Predicted) Mean	Median
Stroke	332	24.1	20.5	-0.21	-0.20
Hip fracture	247	22.7	20.6	-0.33	0.05
Hip replacement	238	23.9	28.6	-0.19	0.16
Other RICs	318	24.8	17.9	-0.27	-0.19
All RICs	338	33.1	29.6	-0.39	-0.12

pass the Shapiro-Wilk test for normality ($p < 0.05$). The Z scores are positively correlated across the four indices, indicating some consistency in relative ranking across the four conditions.

The FIM gain can be predicted based on RIC, initial functional status, time since onset, or other available patient information. This is consistent with the findings of others who have modeled changes in functional status (Carey et al., 1988; Stineman et al., 1995). The Stineman et al. paper also modeled improvement at the hospital level and discusses how such models can be used for quality improvement activities.

There are substantial differences across hospitals in risk-adjusted FIM gain. These differences suggest that it would be useful to monitor gain in functional status for any form of payment for rehabilitation care, which would require that HCFA collect functional status information at both admission and discharge.

RESIDENCE IN SKILLED NURSING FACILITY

The goal of an inpatient stay in a rehabilitation facility is generally to restore sufficient function that a patient can return to the community to live. Unfortunately, this goal is not always achieved and in about 15 percent of cases the patient takes up residence in a SNF instead of in the community. Some of these cases are discharged from rehabilitation to an acute facility, and then go to a SNF rather than return to rehabilitation.

Table 7.5 lists the proportion of UDSmr cases in each FRG for which Medicare received a SNF bill covering a period within 30 days of discharge from a rehabilitation facility.[1] One can see there is a strong relationship between FRG and percentage of cases discharged to a SNF, and little relationship between FRG and the use of home health. The first two digits of the FRG give the RIC, so that the first five FRGs are in RIC 1 (stroke), etc. It is not surprising that persons with stroke have a much higher than average chance of going to a SNF and those with a joint replacement have a much lower than average chance. However, there is also a strong relation between functional status and SNF residence. In general, functional status improves with the last digit of the FRG number, so that patients in FRGs that end in a 1 have less functional independence at admission than those in FRGs that end in a 5. Exceptions to this rule include FRGs 011 and 012, which are

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[1] The end of the data subsection in Section 2 describes the Standard Analytic Files that we used here.

Table 7.5

Percentage of Patients that Entered a Skilled Nursing Facility and Used a Home Health Agency Within 30 Days of Discharge from Rehabilitation, by FRG

FRG	Cases (N)	SNF (%)	HHA (%)
Total	89367	0.14586	0.53383
011	7239	0.31482	0.46982
012	4774	0.41831	0.40155
013	6371	0.16010	0.54214
014	5667	0.07923	0.53838
015	3859	0.03835	0.43483
021	131	0.43511	0.25191
022	290	0.29655	0.37241
023	498	0.11847	0.45984
024	103	0.03883	0.22330
025	98	0.05102	0.31633
031	68	0.26471	0.39706
032	316	0.39873	0.37025
033	629	0.19555	0.47854
034	552	0.10145	0.50181
035	377	0.07427	0.40584
041	80	0.27500	0.46250
042	97	0.27835	0.34021
043	194	0.18557	0.45876
044	121	0.11570	0.53719
045	1460	0.5479	0.39726
051	156	0.30128	0.41667
052	567	0.22575	0.49912
053	594	0.14983	0.56397
054	574	0.07840	0.55401
055	656	0.04116	0.46189
061	1339	0.21060	0.50709
062	1174	0.14225	0.60051
063	851	0.07638	0.56992
064	711	0.03657	0.45148
071	4925	0.29096	0.54335
072	2321	0.15898	0.63723
073	2619	0.09927	0.65101
074	1534	0.06193	0.62777
075	2010	0.04279	0.60896
081	2008	0.17729	0.62948
082	2346	0.06309	0.65345
083	2508	0.03828	0.64354
084	4389	0.01732	0.56345
085	5178	0.01024	0.50560
091	842	0.26841	0.52732
092	1475	0.13153	0.61831
093	1487	0.05514	0.54539

Table 7.5--continued

FRG	Cases (N)	SNF (%)	HHA (%)
101	468	0.14316	0.54274
102	513	0.03899	0.52632
103	223	0.01345	0.47534
111	676	0.16864	0.55769
112	309	0.02913	0.45955
113	288	0.02431	0.35069
121	1159	0.21570	0.53926
122	665	0.12331	0.61353
123	770	0.07273	0.59610
124	987	0.03749	0.52482
131	68	0.20588	0.67647
132	186	0.11290	0.65591
133	11	0.09091	0.36364
141	186	0.25806	0.41398
142	411	0.17275	0.61557
143	987	0.08004	0.64742
144	728	0.01648	0.54121
151	399	0.26316	0.41604
152	416	0.15865	0.58173
153	1106	0.07324	0.47559
161	392	0.14286	0.52551
162	759	0.05665	0.41765
171	39	0.30769	0.43590
172	106	0.20755	0.55660
173	66	0.12121	0.57576
174	111	0.03604	0.54955
181	1582	0.24716	0.50759
182	1596	0.16040	0.59524
183	1197	0.09190	0.60150
184	752	0.05585	0.49202
191	42	0.28571	0.30952
192	93	0.12903	0.53763
193	48	0.00000	0.50000
194	43	0.02326	0.41860
195	6	0.00000	0.00000
201	14	0.14286	0.14286
202	36	0.11111	0.44444
203	8	0.25000	0.25000
204	17	0.11765	0.58824
205	30	0.03333	0.33333

defined by the same functional level but are split by age, with those in FRG 012 being older.

In addition to FRG, the presence of a comorbidity increases the chance that a person will go to a SNF. Although the raw numbers are larger, after controlling for FRG a comorbidity increases the likelihood of SNF residency by 1.8 percent ($t = 6.32$, $p < 0.001$).

The substantial ability of the FRGs to predict differential use of SNFs suggests it likely that one could develop a good risk-adjustment model for this outcome. Although one should have additional clinical and sociological information, the FRGs clearly present a good starting place. Just using the rough risk adjustment derived from FRG and comorbidity, we calculated actual minus predicted SNF residence and transformed the result into a Z score for hospitals with more than 30 cases. Table 7.6 shows that, as before, there are a substantial number of hospitals that have scores both better and worse than predicted by this simple model.

Table 7.6

Distribution of Normal Transformation of Actual Percentage of SNF Residents Minus Predicted, by RIC

RIC	Hospitals (N)	Z < -1.645 (%)	Z > 1.645 (%)
Stroke	286	22.0	17.5
LE Fracture	156	16.0	14.1
LE joint replacement	156	11.5	6.4
Other RIC	263	17.9	20.5
Total	328	26.2	28.1

8. CONCLUSIONS

An RPPS is feasible. The design described in this report appears to achieve its goals. The RPPS provides hospitals with incentives for efficiency because they can keep payments in excess of costs. The RPPS explains about 50 percent of patient-level costs and disadvantages no beneficiary demographic group; it therefore should maintain access to high quality and appropriate care for all Medicare beneficiaries. Depending on the details of the RPPS, payments explain 60 to 65 percent of the variance in costs at the hospital level. The only hospital group systematically disadvantaged by the RPPS are new hospitals that are likely to be in the easiest position to reduce costs because TEFRA cost controls have had less impact on these facilities than on older facilities. We believe the simulation results indicate that the RPPS is fair to hospitals since Medicare payments would be made according to patient characteristics modified by input prices and are close to per discharge costs for all groups of hospitals except those that probably have high costs because they have especially high payments under TEFRA. We provide two suggestions for monitoring outcomes under an RPPS that should be able to detect whether patients are being discharged too early.

If an RPPS were to be implemented, HCFA must plan for improvements in coding. We expect that coding errors exist in our data, particularly undercoding of comorbidities. Based on the acute care PPS experience, we believe coding errors would be reduced over time if HCFA announced its intention to use the FIM-FRGs as a basis for payments and then did so. In the long run, better coding would result in fairer payments.

The distribution of payments in an RPPS is stable in face of changes in the design of an RPPS. Thus, choices can be made based on administrative simplicity and convenience. We recommend using the Medicare definition of a discharge, calculating FRGC weights using the standard method, paying for transfers using the method described in Section 5, and monitoring outcomes.

Facility-level payment adjustments should account for variations across hospitals in market-area wage levels and in percentage of low income patients, perhaps using Medicaid eligibility as a criteria. Although we found no excess costs associated with teaching programs, we would recommend revisiting this question with verified data from the population of all teaching hospitals. This future analysis should also address whether there is an interaction between teaching status and percentage of low income population and/or inner city location.

Outlier payment is an important element of payment design. Including high cost outlier payments strongly improves the fit of payment to cost at the patient and hospital level. They reduce financial risk that would otherwise be substantial because of the relatively small size of many rehabilitation facilities. They reduce losses caused by very expensive patients and therefore reduce incentives to underserve such patients. Low cost outliers allow even better match of payments to costs, and reduce incentives for unnecessary or futile admissions.

There are differences in FIM improvement at the hospital level that are not explained by RIC, initial functional status, time since onset, or other available patient information. There are more facilities with particularly high and particularly low deviations from the mean than would be expected based on chance. We also found similar results for discharges to a SNF. These suggest the probability that there are significant variations across hospitals in performance measures under the current payment system beyond the observed variations in cost.

Given the theoretical drawbacks of the TEFRA system that were discussed in the Introduction and the empirical inequalities in costs and outcomes, it would seem time to change the method of payment for inpatient rehabilitation cases. An RPPS would move care toward a national standard, thus improving equity across patients at the same time that it improves incentives for efficiency and improves equity across facilities.

Appendix

SUPPORTING TABLES

Table A.1

Regression of Log of Hospital Cost per Discharge (Case) on Possible Payment Factors and Case Mix Indices Calculated by Alternative Weights (Case Weighted)

	Standard Weight		UDSmr Case		Cost Weight		HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
CMI	1.406	9.51	1.418	10.13	1.347	9.63	1.291	9.20	1.342	9.57
Log of wage index	0.369	2.92	0.358	2.83	0.344	2.73	0.359	2.80	0.368	2.91
Fraction Medicaid	0.661	3.42	0.652	3.39	0.676	3.52	0.704	3.64	0.657	3.40
Large urban area	0.038	1.07	0.038	1.08	0.044	1.24	0.040	1.13	0.039	1.10
Teaching	0.168	0.88	0.148	0.78	0.145	0.76	0.155	0.81	0.165	0.87
Intercept	9.361	---	9.383	---	9.357	---	9.355		9.321	

NOTE: Based on 341 hospitals. R-squares are 0.32, 0.34, 0.32, 0.31, and 0.32, respectively.

Table A.2

Comparison of Facility Payment Regressions by CMIs Calculated from Alternative Weights (Cost Weighted)

	Standard Weight		UDSmr Case		Cost Weight		HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
Log (wage index)	0.458	4.23	0.453	4.17	0.446	4.14	0.450	4.15	0.458	4.24
Fraction Medicaid	0.824	4.48	0.825	4.49	0.817	4.47	0.819	4.15	0.800	4.37
Intercept	9.365	---	9.389	---	9.366	---	9.361	---	9.338	---

NOTE: R-square is 0.09 on each regression.

Table A.3

Facility Payment Regression Adding Teaching, by CMIs Calculated from Alternative Weights (Hospital Weighted)

	Standard Weight		UDSmr Case		Cost Weight	
Variable	coef.	t-stat	coef.	t-stat	coef.	t-stat
Log (wage index)	0.441	4.24	0.435	4.18	0.430	4.16
Fraction Medicaid	0.824	4.83	0.826	4.83	0.812	4.78
Residents to Census	0.183	1.06	0.187	1.08	0.173	1.01
Intercept	9.370	---	9.393	---	9.370	---

	HSRV Weight		Fair Weight	
Variable	coef.	t-stat	coef.	t-stat
Log (wage index)	0.432	4.15	0.437	4.22
Fraction Medicaid	0.816	4.77	0.802	4.71
Residents to Census	0.164	0.95	0.184	1.07
Intercept	9.368	---	9.341	---

NOTE: R-squares are 0.12, 0.12, 0.11, 0.10, and 0.11

Table A.4

Average LOS and Standard Method Weights for FRGC

	LOS		FRGC Weight	
FRG	With cc[a]	No cc	With cc	No cc
011	27.4	28.5	1.62147	1.62147
012	24.3	25.3	1.40954	1.40954
013	22.5	23.8	1.23856	1.23856
014	17.8	19.1	0.97765	0.97765
015	13.0	14.2	0.71100	0.71100
021	31.6	34.9	2.28908	2.19845
022	27.5	27.2	1.64018	1.57524
023	20.7	21.1	1.22090	1.17256
024	22.3	21.5	1.16059	1.11464
025	11.0	14.1	0.72759	0.69878
031	30.2	29.6	2.07953	1.90531
032	27.5	26.7	1.86735	1.71090
033	22.7	22.0	1.37635	1.26104
034	16.8	18.6	1.11616	1.02265
035	14.5	14.2	0.82654	0.75730
041	43.2	42.1	2.62400	2.50027
042	31.7	29.4	1.78143	1.69743
043	23.9	26.8	1.45175	1.38330
044	27.4	21.0	1.17415	1.11879
045	17.3	18.0	0.93475	0.89067
051	34.9	35.0	2.40903	1.98998
052	31.3	27.0	1.83297	1.51413
053	24.1	22.2	1.38988	1.14811
054	17.7	17.0	1.06196	0.87723
055	15.9	13.3	0.80079	0.66149
061	22.7	21.9	1.36554	1.22734
062	20.4	19.4	1.16311	1.04540
063	16.4	17.3	1.00368	0.90210
064	14.8	14.0	0.81456	0.73213
071	20.9	20.0	1.15106	1.03944
072	18.0	18.2	0.98987	0.89388
073	16.9	16.9	0.90312	0.81554
074	16.4	15.0	0.79179	0.71501
075	14.8	13.6	0.69861	0.63087
081	20.1	17.8	1.16305	0.96016
082	16.5	14.5	0.90569	0.74769
083	14.8	13.6	0.82588	0.68181
084	14.0	11.9	0.72122	0.59541
085	11.2	10.2	0.60138	0.49647
091	20.7	19.6	1.21889	1.06252
092	19.1	17.3	1.01429	0.88417
093	16.2	14.2	0.83572	0.72851
101	18.3	20.4	1.14987	1.08845
102	14.5	15.5	0.83915	0.79432
103	15.3	13.0	0.73193	0.69283

Table A.4--continued

	LOS		FRGC Weight	
FRG	With cc[a]	No cc	With cc	No cc
111	23.9	19.7	1.37133	1.08316
112	16.0	14.6	1.01188	0.79924
113	15.2	11.8	0.81717	0.64545
121	21.0	22.0	1.26068	1.21246
122	22.6	22.2	1.25337	1.20543
123	19.3	18.8	1.03995	1.00017
124	16.5	16.8	0.88183	0.84810
131	21.9	20.1	1.29814	1.27383
132	16.7	16.7	0.91245	0.89537
133	15.5	16.0	0.83482	0.81919
141	22.6	20.6	1.44655	1.25255
142	19.5	18.4	1.14412	0.99068
143	15.2	14.6	0.86244	0.74678
144	12.6	12.2	0.59731	0.51721
151	27.4	22.2	2.07408	1.95994
152	20.1	20.3	1.25862	1.18936
153	15.8	16.3	1.01736	0.96138
161	19.1	18.4	1.14258	0.98244
162	16.5	14.9	0.89594	0.77037
171	29.7	23.7	2.01207	1.60539
172	22.8	20.1	1.28724	1.02706
173	24.8	17.9	1.12661	0.89890
174	18.2	15.22	0.99719	0.79564
181	22.1	20.6	1.28363	1.16613
182	18.2	17.6	1.03359	0.93898
183	15.1	15.2	0.86989	0.79026
184	12.4	12.1	0.70323	0.63886
191	51.7	31.1	2.38673	2.34556
192	37.3	32.0	1.70603	1.67660
193	21.7	19.5	0.99023	0.97315
194	13.6	18.9	0.90615	0.89052
195	.	8.7	.	0.36288
201	22.3	35.9	2.64598	2.46957
202	37.5	27.6	1.70549	1.59178
203	22.0	29.0	1.49340	1.39383
204	22.3	24.7	1.40325	1.30969
205	18.0	16.0	0.89236	0.83286

[a] cc is complication or comorbidity.

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